The Impact of Green Credit on Bank Risk-Taking: Based on the Moderating Effect of FinTech

Yuhan Luo [1,*], Haoxin Tian [2]

[1] Sino-French Institute, Renmin University of China, Suzhou, China, 215123

[2] College of Finance and Statistics, Hunan University, Changsha, China, 410082

* Corresponding Author Email: luoyuhan@ruc.edu.cn

Abstract. Based on panel data from 20 representative listed commercial banks in China between 2015 and 2023, this study conducts an empirical analysis of the effect of green credit on bank risk-taking, with a specific focus on the moderating function of FinTech. The results indicate that green credit plays a significant role in reducing risk exposure among commercial banks. Furthermore, FinTech is found to strengthen this risk-alleviating impact. The inhibitory influence of green credit on risk-taking is also more substantial in large state-owned commercial banks compared to their non-state-owned counterparts. By examining the interplay between green credit and bank risk-taking from a risk-bearing perspective, this research elucidates the facilitatory role of FinTech and offers novel insights and a theoretical foundation for commercial banks to evaluate green credit risks, develop evidence-based risk management frameworks, and optimize policy support systems for green finance.

Keywords: Green credit, Commercial bank risk-taking, FinTech, Moderating effect.

1. Introduction

As a fundamental element of green finance, green credit constitutes a financial innovation wherein commercial banks and other financial institutions incorporate environmental criteria into their lending decisions, offering financial backing to eco-friendly initiatives such as energy conservation, clean energy, and other sustainable projects. Since the introduction of China's "dual carbon" goals, the green credit market has experienced sustained growth. While driving the transition toward a green economy, this expansion has also significantly reshaped the operational and risk management practices of commercial banks. Acting as the main conduits of green credit, the risk-bearing capacity of commercial banks plays a crucial role in safeguarding financial system stability and supporting the long-term viability of green finance. Meanwhile, the rapid advancement of financial technology (FinTech) has significantly reshaped credit processes and risk management models, necessitating further empirical examination of its impact on green credit, commercial bank risk, and associated risk effects. Against this backdrop, an in-depth investigation into the influence of green credit on commercial bank risk and the moderating role of FinTech in this process holds substantial theoretical and practical significance.

This study selects a sample of 20 listed commercial banks in China from 2015 to 2023, including six large state-owned banks and 14 non-state-owned banks, ensuring representativeness across different bank sizes and types. Utilizing balanced panel data, we construct a two-way fixed effects model and a moderating effects model, incorporating a FinTech index as the moderating variable to examine how green credit affects commercial bank risk-taking under the moderating influence of FinTech.

This study contributes to the existing literature in several aspects. From an innovative standpoint, earlier research[1-3] has mainly focused on the effects of green credit on the operational performance or profitability of commercial banks. Differing from these approaches, the present paper empirically analyzes the connection between green credit and bank risk-taking from a risk-bearing perspective. This reframing offers a new pathway for commercial banks to evaluate risk exposures within green lending practices, allowing for a more balanced perception of risks and returns in green finance and supporting the development of more informed risk management policies.

In terms of methodological contribution, although prior studies[4-7] have addressed the influence of FinTech on either green credit or bank risk, little attention has been paid to its moderating role within the specific relationship between green credit and bank risk-taking. By applying a moderation model, this research further explores how FinTech moderates the effect of green credit on commercial bank risk-taking. Such a method not only improves the accuracy of identifying complex interactions among green credit, FinTech, and risk-taking across banks with varying ownership structures, but also offers a crucial theoretical basis for improving policy support systems related to green creditt.

2. Data and model

2.1. Sample Selection and Data Sources

This research is based on a balanced panel comprising 20 publicly traded commercial banks in China over the period from 2015 to 2023. The sample consists of six large state-owned banks—namely Industrial and Commercial Bank of China, Agricultural Bank of China, Bank of China, China Construction Bank, Bank of Communications, and Postal Savings Bank of China—as well as 14 non-state-owned banks, including China Merchants Bank, Shanghai Pudong Development Bank, China Minsheng Bank, Industrial Bank, Ping An Bank, China CITIC Bank, China Everbright Bank, Huaxia Bank, Bank of Beijing, Bank of Nanjing, Bank of Ningbo, Bank of Hangzhou, Bank of Shanghai, and Bank of Jiangsu.

Bank-specific data were obtained from the annual reports issued by these commercial banks, the CSMAR database, and the Digital Inclusive Finance Index developed by the Institute of Digital Finance at Peking University. Macroeconomic data were sourced from the National Bureau of Statistics and other official publications.

2.2. Variable Selection and Definitions

2.2.1. Dependent variable

Drawing on existing studies [1-3], this paper adopts the Z-score as the measure of commercial bank risk. A higher Z-score indicates lower risk-taking and greater stability in banks. The calculation formula is as follows:

$$Z\_score = \ln\left(\frac{\mathrm{ROA+CAR}}{\sigma(\mathrm{ROA})}\right) \tag{1}$$

Where: ROA denotes Return on Assets, reflecting the bank's profitability;

CAR represents Capital Adequacy Ratio, measuring the bank's capital strength; σ(ROA) indicates the standard deviation of Return on Assets, which captures the volatility of the bank's earnings.

2.2.2. Independent Variables

Drawing on previous studies [8-10], this study selects the green credit balance as the core independent variable. The green credit balance has been logarithmically transformed and is represented by its natural logarithm. A larger green credit balance indicates greater bank investment in green credit business and stronger support for green industries.

2.2.3. Moderating Variable

Building upon established research [11-13], this study utilizes the Digital Inclusive Finance Index compiled by Peking University to quantify the level of FinTech development (FINTECH). This index, which is provided at provincial, municipal, and county levels, offers a comprehensive assessment of regional FinTech advancement—with higher index values denoting more developed FinTech ecosystems.

For the six major state-owned commercial banks and the eight nationwide non-state-owned commercial banks, the aggregate national-level Digital Inclusive Finance Index is employed. In the case of the six regional non-state-owned city commercial banks, the corresponding provincial or municipal index values are applied. The reason is based on the following considerations:

National banks adopt the nationwide inclusive finance index to reflect the macro FinTech environment, while regional city commercial banks use local indices to accurately assess their exposure to regional ecosystems. This differentiated indicator selection ensures both data representativeness and research validity (avoiding the omission of key factors resulting from applying a national index to regional banks), and aligns with the accuracy principle of variable measurement in empirical research. Relevant prior studies (e.g., Chen et al., 2023, emphasized the importance of the regional FinTech environment when researching city commercial banks) have validated the rationality of this approach [11] [13]. Its core logic lies in selecting the most representative data level based on the characteristics of the research objects.

2.2.4. Control Variables

Consistent with existing research on bank risk-taking [9][11-12], this study includes the following bank-level control variables:Bank size (*lnSIZE*, Natural logarithm of total assets); Non-performing loan ratio (*NPL*); Capital adequacy ratio (*CAR*); Provision coverage ratio (*PCR*); Return on assets (*ROA*).

At the macroeconomic level, the control variables comprise:Year-on-year GDP growth rate (*GDPR*);Monthly arithmetic average growth rate of M2 money supply (*M2*).

The description of all variables selected in this paper is shown in Table 1.

Table 1. Variable Definitions

Variable type	***Variable name***	***Variable symbol***	***Definition***
Dependent variable	commercial bank risk	*Z_score*	$Z\_score = \ln\left(\frac{\text{ROA+CAR}}{\sigma(\text{ROA})}\right)$
Independent Variables	green credit balance	*lnGL*	The natural logarithm of green credit balance
Moderating Variable	FinTech Index	*FINTECH*	Digital Inclusive Finance Index
Control Variables	Bank size	*lnSIZE*	Natural logarithm of total assets
	Non-performing loan ratio	*NPL*	(Gross NPL Amount / Total Gross Loans) × 100%
	Capital adequacy ratio	*CAR*	(Net Capital / Total Risk-Weighted Assets) × 100%
	Provision coverage ratio	*PCR*	(Loan Loss Provisions / Gross Non-performing Loans) × 100%
	Profitability ratios - Return on assets	*ROA*	(Net Profit / Average Total Assets) × 100%
	Year-on-year GDP growth rate	*GDPR*	Year-on-year GDP growth rate(expressed in percentage terms)
	Monetary policy	*M2*	Monthly arithmetic mean growth rate of money supply (expressed in percentage terms)

2.3. Model Specification

To more thoroughly examine the relationship between green credit and bank risk—specifically, the impact of green credit on commercial bank risk-taking—this study employs a two-way fixed effects panel regression model incorporating both entity fixed effects and time fixed effects:

$$\text{Zscore}_{it} = \alpha_0 + \alpha_1 \ln \text{GL}_{it} + \boldsymbol{\zeta}\mathbf{Control} + \mu_i + \gamma_t + \varepsilon_{it} \quad (2)$$

Where: "*i*"denotes the i-th bank; "*t*" indicates the t-th year; α_0 is the constant term; $\boldsymbol{\zeta}$ represents the regression coefficients; $\boldsymbol{Control}$ refers to the control variables; $\mu_i$captures bank fixed effects; $\gamma_t$represents time fixed effects; ε_{it} is the random error term.

To further investigate the moderating effect of financial technology (*FinTech*) on bank risk, we augment the baseline regression model by incorporating both the moderating variable and its interaction term, specified as follows:

$$Zscore_{it} = \beta_0 + \beta_1 \ln GL_{it} + \beta_2 Fintech_{it} + \beta_3 \ln GL_{it} \times Fintech_{it} + \boldsymbol{\zeta Control} + \mu_i + \gamma_t + \varepsilon_{it} \quad (3)$$

Where: β_0 is the constant term; β_1, β_2, β_3, and $\boldsymbol{\zeta}$ represent regression coefficients; $ln\,GL_{it} \times Fintech_t$ denotes the interaction term between green credit and FinTech.

3. Empirical Data Analysis

3.1. Descriptive Statistics

Table 2 displays the descriptive statistics for the key variables included in the study. It can be observed that the dependent variable, bank risk-taking (Z_score), has a mean value of 5.110 and a median of 5.109, which are closely aligned. The small standard deviation further suggests generally stable risk profiles and a symmetrical distribution across the sample of banks. The minimum value (4.070) remains well above the bankruptcy threshold, reflecting listed banks' strong risk management capacity.

For the independent variable, green credit *(lnGL*), the mean (7.154) is significantly lower than the median (7.353), with a standard deviation of 1.739 and a range of 8.244. The moderating variable, FinTech (*FINTECH*), exhibits the most pronounced dispersion—its mean (274.489) is slightly below the median (280.800), and the range reaches 1,110.

The sample data reveal substantial heterogeneity among Chinese commercial banks in green credit scale and FinTech development levels, while control variables such as bank risk-taking and capital adequacy ratios generally fall within reasonable ranges. This diversified sample characteristic provides an empirical foundation for examining the relationship between green credit and bank risk.

Table 2. Descriptive Statistics of Key Variables

Variable	***Obs.***	***Mean***	***S.D***	***Min***	***Median***	***Max***
Z_score	180	5.110	0.407	4.070	5.109	5.821
lnGL	180	7.154	1.739	2.653	7.353	10.897
FINTECH	180	274.489	173.268	40.000	280.800	1150.000
lnSIZE	180	29.325	1.112	26.496	29.418	31.431
CAR	180	13.831	1.819	10.460	13.450	19.260
PCR	180	240.271	101.264	132.440	204.840	567.710
NPL	180	1.396	0.333	0.680	1.430	2.390
ROA	180	0.829	0.177	0.416	0.819	1.374
GDPR	180	5.891	1.929	0.700	6.600	8.600
M2	180	10.267	1.586	8.300	10.400	13.100

3.2. Correlation Analysis

Table 3 presents the correlation coefficients obtained through Spearman correlation analysis. Based on the values displayed, green credit exhibits a statistically significant association with commercial bank risk-taking, suggesting that an expansion in green credit is associated with a reduction in bank risk exposure. As a moderating variable, financial technology (FINTECH) displays a correlation coefficient of 0.197 with the Z_score, which is significant at the 1% level and positive in direction. This implies that advancements in financial technology are strongly linked to lower levels of risk in banking institutions.

The multicollinearity test demonstrates that all pairwise correlation coefficients remain below the threshold of 0.7 in absolute value, falling within an acceptable range. This confirms the absence of

severe multicollinearity among variables, establishing a robust foundation for subsequent regression modeling.

The correlation analysis preliminarily verifies the expected associations among green credit, FinTech, and bank risk, that is, both green credit and FinTech may reduce bank risk, and the linear relationships between variables are not disturbed by severe multicollinearity.

Table 3. Correlation Analysis

	Z_score	*lnGL*	*lnSIZE*	*NPL*	*CAR*	*PCR*	*ROA*	*GDPR*	*M2*	*FINTECH*
Z_score	1									
lnGL	0.245**	1								
lnSIZE	0.057	0.594***	1							
NPL	-0.544***	-0.010	0.114	1						
CAR	0.048	0.521***	0.361***	-0.076	1					
PCR	0.408***	-0.104	-0.270***	-0.648***	0.118	1				
ROA	-0.133*	0.174**	0.191***	0.011	0.384***	0.143*	1			
GDPR	-0.043	-0.258***	-0.205***	0.104	-0.184**	-0.073	0.114	1		
M2	-0.049	-0.040	-0.035121	-0.028	-0.154**	-0.044	0.056	-0.249***	1	
FINTECH	0.197***	0.076	-0.189**	-0.440***	0.149**	0.431***	-0.212***	-0.276***	-0.207***	1

Note: The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

4. Empirical Results Analysis

4.1. Baseline Regression Results

The baseline regression analysis employs a two-way fixed effects model to assess the primary relationship between green credit and commercial bank risk-taking. Table 4 displays estimation outcomes for both Model (1), which serves as the baseline, and Model (2), incorporating the full set of control variables, under varying specifications of time and entity fixed effects. As presented in column (1), the coefficient for the key independent variable lnGL is 0.046 and statistically significant at the 1% level, suggesting that an increase in green credit balance is strongly associated with elevated bank risk-taking in the absence of control variables.

Column (2) extends the analysis by adding control variables while omitting year fixed effects. Here, the coefficient on lnGL declines to 0.008 yet remains positively significant at the 1% level, implying that green credit continues to contribute to risk mitigation even after controlling for bank-specific features and macroeconomic conditions. Further incorporating year fixed effects in column (3) yields a coefficient of 0.010 for lnGL, which is again significant at the 1% level, affirming the consistency of green credit's risk-reducing influence.

Overall, the baseline regression estimates confirm a statistically significant and positive association between green credit and commercial banks' Z-scores of risk-taking across different model specifications. This supports the conclusion that expanding green credit can meaningfully lower bank risk, thereby providing a reliable basis for further investigation into the moderating role of FinTech.

Table 4. Baseline Regression Results

	(1) *Z_score*	*(2)* *Z_score*	*(3)* *Z_score*
lnGL	0.046***	0.008***	0.010***
	(0.011)	(0.002)	(0.003)
lnSIZE		-0.029***	-0.010
		(0.009)	(0.013)
NPL		0.002	0.000
		(0.005)	(0.005)
CAR		0.066***	0.066***
		(0.001)	(0.001)
PCR		-0.000	-0.000
		(0.000)	(0.000)
ROA		0.085***	0.081***
		(0.008)	(0.009)
GDPR		-0.001	0.001
		(0.000)	(0.002)
M2		-0.002***	0.007
		(0.000)	(0.005)
Constant	5.172***	4.949***	4.415***
	(0.083)	(0.260)	(0.436)
Bank FE	Yes	Yes	Yes
Year FE	Yes	No	Yes
N	180	180	180
adj. R-sq	0.409	0.987	0.987

Note: The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are provided in parentheses.

4.2. Robustness Tests

To ensure the robustness of the baseline regression results regarding the inhibitory effect of green credit on commercial bank risk-taking, this study employs two alternative approaches: truncating the sample period and lagging the dependent variable by one period (t+1). The corresponding results are reported in Table 5.

Column (1) displays outcomes after restricting the sample period to 2015–2019, thereby excluding the potential influence of the COVID-19 pandemic and its aftermath. This adjustment helps mitigate distortions caused by extreme exogenous shocks. The coefficient of the green credit variable (lnGL) remains positive and statistically significant at the 1% level, with a value of 0.008. This suggests that even over a shorter time frame, green credit continues to significantly suppress risk-taking among commercial banks, corroborating the baseline findings.

In Column (2), the dependent variable is shifted to the next period (t+1). The coefficient on lnGL is 0.007 and significant at the 1% level, indicating that current green credit investments contribute to a reduction in bank risk in the subsequent period. This result further supports the conclusion that green credit exerts a stable and persistent inhibitory effect on bank risk-taking, aligning consistently with the initial regression evidence.

Table 5. Robustness Tests

	(1)	*(2)*
	Z_score	*Z_score(t+1)*
lnGL	0.008***	0.007***
	(0.002)	(0.002)
lnSIZE	0.005	-0.012
	(0.017)	(0.015)
CAR	0.071***	0.069***
	(0.001)	(0.002)
PCR	-0.000**	-0.000*
	(0.000)	(0.000)
NPL	0.011**	0.013
	(0.005)	(0.006)
ROA	0.110***	0.105***
	(0.015)	(0.016)
GDPR	0.009**	0.008*
	(0.004)	(0.004)
M2	0.001	-0.003
	(0.002)	(0.003)
Constant	3.756***	3.982***
	(0.498)	(0.521)
Bank FE	Yes	Yes
Year FE	Yes	Yes
N	100	160
adj. R-sq	0.991	0.986

Note: The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are provided in parentheses.

4.3. Moderating Effect Analysis

The moderating influence of FinTech on the linkage between green credit and bank risk-taking is summarized in Table 6. Column (1) displays regression outputs without control variables; Column (2) incorporates control variables but excludes year fixed effects; and Column (3) reports results from the full model that includes both control variables and year fixed effects.

Across all three specifications, the coefficients for FinTech (FINTECH) are positive and statistically significant, suggesting that FinTech development independently contributes to the reduction of commercial bank risk-taking. Furthermore, the interaction term between green credit and FinTech (lnGL×FINTECH) also exhibits significantly positive coefficients throughout columns (1) to (3), implying that FinTech strengthens the risk-mitigating influence of green credit.

These findings indicate that the beneficial effect of green credit in lowering bank risk is more substantial in contexts where FinTech infrastructure is more advanced.

Table 6. Moderating Effects

	(1) *Z_score*	*(2)* *Z_score*	*(3)* *Z_score*
lnGL	0.025*	0.010***	0.011***
	(0.014)	(0.003)	(0.003)
FINTECH	0.001***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
lnGL_FINTECH	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
lnSIZE		-0.029***	-0.028
		(0.010)	(0.016)
CAR		0.067***	0.068***
		(0.002)	(0.002)
PCR		-0.000	-0.000
		(0.000)	(0.000)
NPL		0.003	0.002
		(0.007)	(0.008)
ROA		0.073***	0.073***
		(0.013)	(0.019)
GDPR		0.000	0.001
		(0.000)	(0.001)
M2		0.000	0.003
		(0.001)	(0.008)
Constant	5.146***	4.868***	4.801***
	(0.138)	(0.293)	(0.563)
Bank FE	Yes	Yes	Yes
Year FE	Yes	No	Yes
N	180	180	180
adj. R-sq	0.409	0.987	0.987

Note: The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are provided in parentheses.

4.4. Heterogeneity Analysis

Table 7 summarizes the estimated effects of green credit on bank risk-taking categorized by ownership type. The regression outputs are organized into two groups: estimates for state-owned banks are provided in columns (1) to (2), while those for non-state-owned banks are shown in columns (3) to (4). Among these, columns (1) and (3) reflect the baseline model without control variables, and columns (2) and (4) incorporate the full range of control variables.

Notably, the coefficients of lnGL across all columns are statistically significant and positive, indicating that green credit contributes to reduced risk-taking in both state-owned and non-state-owned banks. Furthermore, the estimated coefficients in columns (1) and (2) are larger in magnitude compared to those in columns (3) and (4), implying that the risk-mitigating effect of green credit is more substantial within state-owned commercial banks.

These findings support the view that state-owned banks, benefiting from greater resource endowments and policy support, are able to leverage green credit lending more effectively to enhance their risk resilience.

Table 7. Heterogeneity Analysis

	(1)	(2)	(3)	(4)
	Z_score	*Z_score*	*Z_score*	*Z_score*
	SOE	*SOE*	*NON-SOE*	*NON-SOE*
lnGL	0.111***	0.025***	0.034***	0.015***
	(0.008)	(0.005)	(0.007)	(0.003)
lnSIZE		0.073**		0.012*
		(0.033)		(0.012)
CAR		0.058***		0.070***
		(0.002)		(0.001)
PCR		-0.000		0.000
		(0.000)		(0.000)
NPL		-0.018***		0.001
		(0.006)		(0.005)
ROA		0.178***		0.041***
		(0.017)		(0.009)
GDPR		0.002		0.000
		(0.003)		(0.002)
M2		0.002		0.016***
		(0.007)		(0.005)
Constant	4.133***	1.820*	4.886***	3.564***
	(0.075)	(0.937)	(0.044)	(0.378)
Bank FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	54	54	126	126
adj. R-sq	0.766	0.998	0.072	0.992

Note: The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are provided in parentheses.

5. Conclusions and Policy Implications

Based on a comprehensive empirical analysis of data from 20 listed commercial banks in China between 2015 and 2023, this research investigates the influence of green credit on commercial bank risk, along with the moderating role of financial technology (FinTech). The study leads to several key conclusions: green credit exhibits a notable risk-reducing influence on commercial banks, with this effect being particularly evident in large state-owned institutions. Additionally, the advancement of FinTech not only contributes independently to lower bank risk-taking but also significantly reinforces the risk-mitigating function of green credit.

Building on these findings, we propose targeted strategies for both commercial banks and government regulators to promote the stable development of the banking and financial system:

(1) Recommendations for Commercial Banks

First, deepen the layout of green credit: Large state-owned banks should leverage their scale and resource advantages to increase investment in green projects and play a leading and exemplary role; small and medium-sized banks need to combine regional and industrial characteristics to develop differentiated green financial products and form a pattern of misplaced competition.

Second, Strengthen the application of financial technology: Accelerate the integration of green finance and financial technology, build a new informatized, digitalized and intelligent financial

platform through the "finance + technology" model, and enhance the ability of green development and high-quality development.

(2) Recommendations for Government Regulatory Authorities

First, improve green finance incentive mechanisms: Reduce the cost of green credit for banks through tax incentives, subsidies, risk compensation and other measures; establish a unified national green project certification standard and information sharing platform to reduce information asymmetry.

Second, optimize the regulatory framework for financial technology: Balance innovation and risk, formulate differentiated regulatory rules, provide more pilot spaces for the technical applications of small and medium-sized banks, and encourage them to enhance their green financial service capabilities through financial technology.

Finally, strengthen policy coordination and guidance: Promote cross-departmental collaboration, integrate the development of green credit into regional economic planning, guide capital flows to low-carbon fields, and help achieve the "dual carbon"goals.

Through the two-way efforts of proactive actions by commercial banks and policy guidance by the government, a positive cycle of coordinated development between green finance and financial technology can be formed, ultimately achieving the dual goals of high-quality economic development and controllable financial risks.

Reference

[1] Wang Y. & Zhi Q., The impact of green lending on credit risk in China, Sustainability, Volume 10, Issue 6, June 2018.

[2] He L., Zhang L., Zhong Z., Wang D. & Wang F., Green credit policy and corporate access to bank loans in China: The role of environmental disclosure and green innovation, Energy Economics, Volume 104, June 2021.

[3] Zhang D., Zhang Z. & Managi S., Does green credit affect the financial performance of commercial banks in China?, Emerging Markets Finance and Trade, Volume 56, Issue 15, 2020.

[4] Zhong K., et al. (2023). The Impact of FinTech on Green Credit: Empirical Evidence from Commercial Banks [J]. Foreign Economics & Management, November 2023.

[5] Ren B., et al. (2021). The Influence of FinTech on Commercial Bank Risk-Taking: A Perspective from Bank Credit Structure [J]. Journal of Financial Economics, 5, 2021.

[6] Zhu S., et al. (2024). The Double-Edged Sword Effect of FinTech on Bank Risk-Taking: The Moderating Role of Macroprudential Regulation [J]. Contemporary Economic Management, May 2024.

[7] Yu B., et al. (2021). Green Credit, FinTech and Commercial Bank Profitability [J]. Finance Horizons, 14.038, 2021.

[8] Liu G., Zhu S. & He L., Green credit policy and systemic risk in the banking sector, Journal of Financial Stability, Volume 65, April 2023.

[9] Wang X., Zhang H. & Huang J., Green credit policy and bank risk: Evidence from China, Energy Economics, Volume 132, December 2023.

[10] Li W.,Zheng M. & Lu X., Does green credit reduce bank risk? Evidence from China's banking sector, Finance Research Letters, Volume 54, January 2023

[11] Wang F., Zhang J.& Zheng X., Digital finance, environmental regulation and bank green innovation: Evidence from China, Energy Economics, Volume 126, Part A, October 2023.

[12] Li X., Huang J.& Chen K., FinTech, green credit and bank risk-taking: Evidence from China, Technological Forecasting and Social Change, Volume 58, Volume 193, August 2023.

[13] Chen S., Li R.& He W., The role of digital finance in fostering green credit: Evidence from Chinese city commercial banks, Journal of Environmental Management, Volume 348, December 2023.

[14] Yanchao Feng et al., Assessing the effect of green credit on risk-taking of commercial banks in China: Further analysis on the two-way Granger causality [J]. Journal of Cleaner Production,437 (2024) 140698.