

How Green Credit Policy Affects Commercial Banks' Credit Risk? Evidence and Federated Learning-Based Modeling From 26 Listed Commercial Banks in China

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ABSTRACT

The green credit policy has significantly influenced the growth of green industries in China. This study evaluates its impact on reducing bank credit risk using data from 26 Chinese banks from 2015 to 2021. The authors discovered that the policy's primary effect is linked to banks' financial leverage. Notably, green credit's influence on insolvency risk is most evident in leverage risk. However, despite governmental support for green credit collaboration, prevalent information gaps between banks and green enterprises lead to misjudgments and subsequent credit losses. To address the balance between credit risk mitigation and privacy, the authors investigated vertical joint learning for a precise risk control model grounded in commercial banks' practices. Experiments revealed that this joint model outperforms the sole "bank internal model" in presenting green credit data, underscoring the potential of machine learning to refine green credit systems and bolster banks' credit risk management.

KEYWORDS

Dynamic Characteristics, Federated Learning, Green Credit Policy, Green Innovation, Risk Management, Risk of Commercial Banks

1. INTRODUCTION

Under the guidance of the "five-in-one" system for building ecological civilization and the "innovation, coordination, green, openness, and sharing" development concept for environmental protection, the Chinese government has issued a series of policy guidelines to protect the environment (Xue et al., 2020; Wang et al., 2019). In 2007, the State Environmental Protection Administration, the People's Bank of China, and the China Banking Regulatory Commission jointly adopted the "Proposal on the Implementation of Environmental Protection Measures and Regulations to Prevent Credit Risks,"

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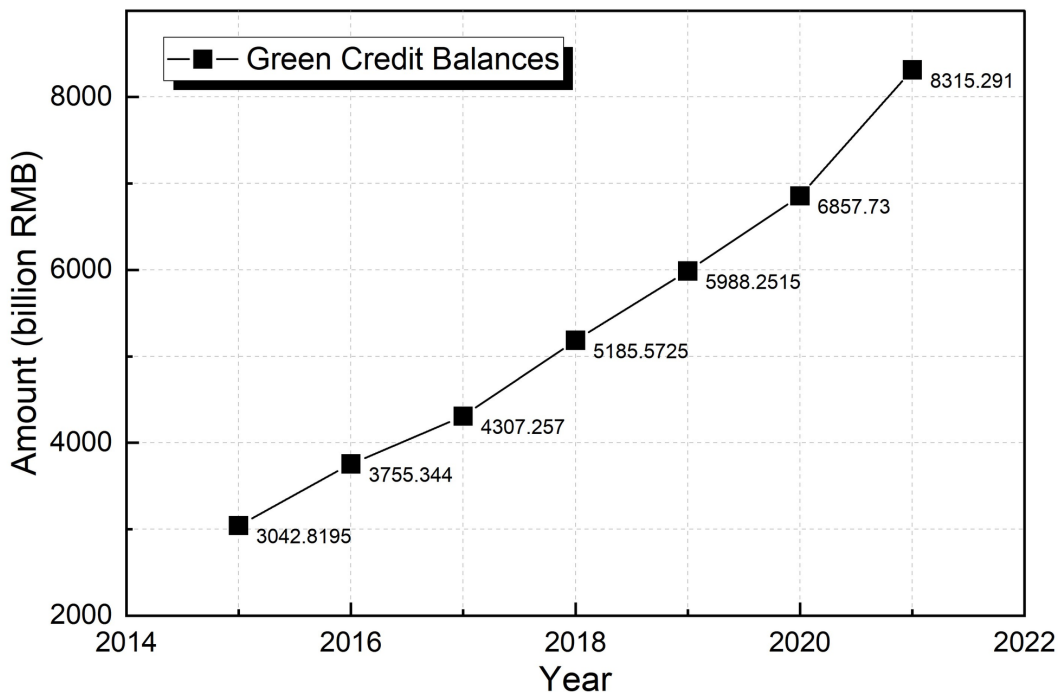
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marking the beginning of China’s comprehensive implementation of the “green credit” policy (Sun et al., 2019). Since then, the green loan balance of China’s commercial banks (five large state-owned banks, 12 joint-stock banks, and some municipal banks) has increased year after year. As Figure 1 shows, the total value of green loans issued by Chinese commercial banks increased from 3042.8195 billion yuan in 2015 to 8315.291 billion yuan in 2021. The green credit policy requires financial institutions, when making loans to consider not only the credit status of enterprises, but also their environmental impact (Chai et al., 2022). Financial institutions are expected to actively support companies that adopt environmentally friendly practices and penalize those that violate national environmental protection policies. In recent years, the state has established the green credit cooperation mechanism and encouraged banks at all levels to cooperate with several commercial banks (Jou et al., 2015; Eisner, 2004). However, there is a serious problem of information asymmetry between banks and companies, which can lead to greenfield companies’ deliberately concealing their true situation when applying for loans. This makes it difficult for banks to effectively assess their credit situation, resulting in credit losses and high credit risk (He et al., 2022; Yang et al., 2020; Sattler et al., 2020). The lack of a unified mechanism for risk identification in the financial system has further weakened the enthusiasm of some banks to make green loans, thus hindering the development of green credit. Therefore, there is an urgent need to address how to reduce corporate default rates, improve information transparency between banks and companies, and avoid bank credit risk. These issues need further research and discussion in the Chinese banking sector (Pillulta et al., 2022; Zhang et al., 2023).

Moreover, the impact of green loans on banks’ credit risk is complex, with different outcomes such as positive, negative, and nonlinear effects. Therefore, commercial banks need to adjust their risk management models to account for these different effects.

At present, however, there are still many debates among scholars about the meaning of green credit, green credit for commercial banks’ credit risk, and the mechanism for developing green credit. On the positive side, the implementation of green credit policies by commercial banks can effectively

Figure 1. Change in total green credit balances of 26 commercial banks, 2015–2021 (in billions)



prevent the emergence of nonperforming loans, manage environmental risks, and reduce risk costs and operational risks. From the perspective of climate finance, green bonds for green projects with high public benefits have more advantages in risk control and cost than traditional projects have (Eshet, 2017; Gu X, 2022; Wu X, 2023; Lian Y, 2022). On the negative side, commercial banks might initially attract more green industries by offering lower interest rates, but they might also lose profits by losing some of their traditional “double-down” corporate customers (Klocke-Daffa, 2022; Biswas, 2016; Li, 2008; Yan et al. 2019). As can be seen, existing studies have focused mainly on the relationship between green credit and commercial bank risk-taking (Eisner, 2004; Klingenberg et al., 2013; Pham, 2021). Although some studies have examined whether green credit can reduce commercial bank risk, there is a lack of discussion on the specific channels through which green credit affects bank risk and the establishment of mechanisms to identify bank risk.

To thoroughly investigate the impact of green loans on commercial bank risk and test the feasibility of a banking risk identification mechanism, this paper further analyzes the impact of green loans on commercial bank risk by decomposing the risk of the investment portfolio. In view of the serious information asymmetry between banks and enterprises, this paper is based on federated learning, a kind of “available and invisible” method for realizing data utilization and modeling with machine learning using the technical support of data security measures. With this method, big data compliance cooperation can be carried out while maintaining data privacy; in addition, the problem of data silos is effectively solved, and banks and green enterprises can cooperate without sharing data. Banks and green enterprises can conduct joint modeling without sharing data to improve commercial banks’ judgment on the credit status of green banks, improve information transparency between banks and enterprises by building accurate risk control models through vertical federated machine learning, increase banks’ enthusiasm for green loans, and further promote the development of green loans.

2. THEORETICAL ANALYSIS AND RESEARCH HYPOTHESIS

2.1 Analysis of the Impact of Green Credit Policy on Commercial Banks’ Credit Risk

The impact mechanism and channels of green credit policy on bank credit risk are diverse. Commercial banks’ green credit policies have two different effects on banks’ risk-taking, which means the implementation of green credit policies may reduce banks’ business risks or may increase them. The process can be explained by the “policy-behavior-risk” transmission mechanism (Xu, 2023; Gao, 2022).

From an investment structure perspective, after banks implement green credit policies, they reallocate credit resources and put severe restrictions on loans to “two high and one leftover” enterprises. This shift in investment direction is driven by banks seeking loan support. To avoid pollution caused by outdated technology, the “two high and one leftover” enterprises actively transform and upgrade through technological innovation and equipment upgrading. Banks provide financial support to these enterprises, improving their performance levels and reducing their losses due to environmental regulations. Green credit has a significant financing penalty effect and investment disincentive effect (Campello & Graham, 2013; Twidell & Cabot, 2003; Miles et al., 2000). However, it can also reduce bank operating risks by reducing the rate of nonperforming loans, increasing the size of the financial asset structure, and accelerating bank financial innovation.

From a risk cost perspective, commercial banks implement green credit policies with higher and stricter standards to review the qualification and the financial and technological innovation of enterprises (Khlif et al., 2015; Qiu et al., 2016). For government-supported enterprises, banks provide preferential credit rates and conditions. Companies in government-restricted industries face strict approval conditions and credit constraints from banks. This effectively protects banks from credit default risk.

From a reputation risk perspective, it is relevant that with increasingly serious environmental problems, the government has introduced policies to encourage green development. Commercial banks can enhance their social reputation and accumulate more moral capital by taking responsibility for

environmental protection through an increase in the scale of green credit allocation. This helps them build a positive public image, reducing their reputation risks (Lemmon & Roberts, 2010; Aintablian, 2007). Based on the above analysis, Hypothesis 1 is proposed:

Hypothesis 1. *The increase of green credit can effectively reduce the business risk of commercial banks.*

2.2 The Risk Reduction Effect of Green Credit Placement on Banks in the Future

To ensure their safety and profitability, banks will adjust their credit structure by reducing loans to enterprises in the “two high and one leftover” sectors while increasing the credit scale for enterprises in green industries. Although the green credit business is a new direction for commercial banks that meets the needs of more green enterprises and brings business advantages and profits, it can also affect the risk-taking level of commercial banks due to high leverage and maturity mismatch issues. This impact may negatively affect the risk of different commercial banks in the short term, given the differences among them. However, over time, the positive impact of green credit on bank risk will gradually increase with the improvement of national policies, bank refinancing, and innovative capital market instruments; the growth of innovative green project guarantees; and the establishment of green funds and a green project database. The quality of enterprises’ environmental information disclosure will also improve, thus reducing the bank risk due to information asymmetry (Li, 2022; Zhang, 2022). As environmental policies improve, people’s demand for green ecology will increase, giving green industries greater development opportunities and stability in profitability. Additionally, strict national environmental policies will accelerate the transformation of “two high and one leftover” enterprises or their withdrawal from the market. Although commercial bank credit may initially trigger a greater risk of default due to the operating difficulties of these enterprises, the credit risk of banks can be significantly reduced once the risks of these enterprises are fully exposed (Godfrey, 2009). Based on this analysis, Hypothesis 2 is proposed:

Hypothesis 2. *The risk-reducing effect of green credit placement on banks will be more obvious in the future.*

3. METHODOLOGY

In this section, we describe the empirical design and data sources of this study on the impact of green credit on bank risk.

3.1 Model Setting and Sample Selection

To illustrate the impact of green credit on bank risk, the following model was developed using the ordinary least squares (OLS) method (Scholtens & Dam, 2007):

$$RISK_{it} = \beta_0 + \beta_1 GREEN_{it} + \beta_2 SIZE_{it} + \beta_3 NIM_{it} + \beta_4 LDR_{it} + \beta_5 NI + \beta_6 NGDP_{it} + \varepsilon_{it} \quad (1)$$

3.1.1 Explanatory Variables

Green Credit (GREEN): Credit funds have traditionally been the main source of funding for Chinese enterprises, and green credit funds can objectively reflect the scale of commercial banks’ participation in green projects. On the basis of data availability and objectivity, this chapter adopts the ratio of banks’ green credit to total loan size to reflect the degree of green credit development.

3.1.2 Response Variables

Bank Risk (RISK): Referring to existing studies, there is no single accepted indicator that can comprehensively portray bank risk. In previous studies, the proxy variables for bank risk mainly included the non-performing loan ratio, net profit, non-interest income, and Z-score (Bian et al., 2015; Delpachitra & Lester, 2013). To examine the impact of bank green credit on bank risk, this paper selects the Z-score measure of bank risk-taking:

$$Zscore_{it} = \frac{ROA_{it} + CAR_{it}}{\delta(ROA_{it})} \quad (2)$$

Where CAR is the capital adequacy ratio of a bank, ROA is the total asset yield of the bank, and $\delta(ROA_{it})$ is the standard deviation of the return on total assets, which reflects the stability of bank profitability (Darrell et al., 1997). i and t denote sample banks and time, respectively. This paper draws on the fact that Z-score is an inverse indicator of bank risk-taking; i.e., the larger the Z-score value, the more stable the banking system and the lower the risk of insolvency. To avoid the influence of the spiky thick-tailed nature of Z-score, this paper takes the natural logarithm of the Z-score.

3.1.3 Control Variables

In the process of studying the impact of green credit policy on the risk of commercial banks, there are some other control variables that could affect the research results. To effectively control these variables, this paper selects the following control variables with reference to previous related research studies both at home and abroad.

- Enterprise Size (*SIZE*): According to the theory of economies of scale, enterprise size and scale effect are positively correlated (Stigler, 1958). In addition, existing academic studies show that an increasing scale of a firm can improve its capital strength, resource abundance, and risk-taking capacity (Saunders et al., 1990).
- Loan-to-Deposit Ratio (*LDR*): This value is replaced with the ratio of total bank loans to total deposits. The level of bank profitability is related to the liquidity position of the funds. In empirical studies, bank liquidity status is often used as a control variable in analytical studies (Faulkender & Petersen, 2006). The *LDR* needs to be stabilized in the right range. Too high a ratio will lead to poor liquidity, difficult liquidity, and increased management risk, while conversely, too low a ratio will lead to poor profitability and make it difficult for banks to gain an edge on the competition.
- Net Interest Margin (*NIM*): Net interest income/interest-earning assets can be used to measure the level of the net interest margin of commercial banks. An increase in credit risk can significantly heighten the risk for commercial banks, which in turn can lead to a decrease in the net interest margin. To maintain stable income, commercial banks may need to strengthen credit risk management to drive business restructuring and business model transformation (Schipperus & Mulder, 2015).
- Bank Noninterest Income (*NI*): This indicator is measured by the interest income/operating income ratio and reflects the income structure of the bank (DeYoung, 2001). There is a substitution relationship between a bank's noninterest income and net interest margin. A higher value indicates that the bank has a larger share of non-interest income, and therefore, the bank is more likely to improve its compensation level by enhancing risk management.
- Return on Total Assets (*ROA*): Empirical research shows that if a company has strong profitability, good operating conditions, and good financial performance, it will have some risk-taking ability (Wang, 2014).

- GDP Growth Rate (*NGDP*): On the basis of on empirical studies, this variable is mostly used as the logarithm of GDP growth rate to represent economic development. In this paper, we expect the effect of this variable on bank risk to be positive.

This paper selects 26 listed commercial banks from 2015 to 2021 as the research sample to study whether the implementation of green credit policy is beneficial to the sustainable development of banks by analyzing the impact of bank green credit balance on bank credit risk. The green credit balances are obtained from the annual reports and social responsibility reports disclosed by each bank on its official website, and the data of bank risk indicators and control variables are obtained from the CSMAR database, the CNDRS database and official reports issued by the Chinese government. Among them, due to the outbreak of the nova coronavirus pandemic in 2020, the probability of corporate default increased, and the state’s policy financial support partially shifted to epidemic prevention and control, so this paper argues that the pandemic circumstances led to frequent adjustments in economic policy that will affect the amount of green credit and other variables of the data for each commercial bank after 2021, and ultimately this paper selects the data as of 2021.

4 EMPIRICAL TEST

4.1 Descriptive Statistics

Using STATA software, the results of the descriptive statistical analysis of each variable are shown in Table 2, from which it can be observed that the natural logarithm of bank risk-taking (*lnZscore1*) has a mean value of 9.135, a minimum value of 8.917, a maximum value of 9.393, and a standard deviation of 0.099, which shows a significant difference, indicating that there are considerable differences in the level of risk-taking among different banks. The mean value of bank green credit (*GREEN*) is 0.031, with a maximum value of 0.1, a minimum value of 0, and a standard deviation of 0.031, indicating that the current participation of Chinese commercial banks in green credit policy is still low and the proportion of green credit is low. It also suggests that there are significant differences in the implementation of green credit policy among banks. Moreover, the standard deviations of all variables are smaller than the mean, indicating that the dispersion coefficients are relatively small and the data stability is good. The descriptive statistics of other variables are mostly within a reasonable range, and the impact of outliers on the empirical results can be excluded.

Table 1. Definition table of control variables

Variable Name	Variable Symbol	Variable Definition
Bank Risk	<i>lnZscore1</i>	The Z-score is chosen to measure bank risk-taking, and the paper takes the logarithm of the Z value
Green Credit	<i>GREEN</i>	Green Credit Scale/Total Loan Scale
Size	<i>SIZE</i>	Total assets at the end of each year are taken as the natural logarithm
Return on Total Assets	<i>ROA</i>	Net Profit/Total Assets
Net Interest Margin	<i>NIM</i>	Net Interest Income/Interest-Earning Assets
Loan-to-Savings Ratio	<i>LDR</i>	Loan Balance/Deposit Balance
GDP Growth Rate	<i>NGDP</i>	GDP growth rate of the province where the commercial bank is incorporated
Bank Noninterest Income	<i>NI</i>	Interest Income/Operating Income

Table 2. Meaning of variables and descriptive statistics

Variable Name	Variable Definition	Sample Size	Average Value	Sd	Min	Max
<i>lnZscore1</i>	Z-score values measure bank risk-taking	185	9.135	0.099	8.917	9.393
<i>GREEN</i>	Green Credit Scale/Total Loan Scale	185	0.031	0.031	0	0.1
<i>SIZE</i>	Natural Logarithm of Total Assets at the End of Each Year	185	28.082	1.664	25.28	31.191
<i>ROA</i>	Net Profit/Total Assets	185	0.008	0.002	0.005	0.013
<i>NIM</i>	Net Interest Income/Interest Earning Assets	185	2.172	0.37	1.25	3.7
<i>LDR</i>	Loan Balance/Deposit Balance	185	79.765	14.573	42.19	116.235
<i>NI</i>	Interest Income/Operating Income	185	24.272	9.569	4.78	51.09

4.2 Baseline Regression Analysis

Table 3 presents the regression estimation results with bank credit risk as the dependent variable. Models (1) to (4) are used separately, controlling for different variables step by step, and a mixed-effects model is used for each model. In terms of p-values, all four models pass the test. After adding all control variables, the goodness of fit of green credit to bank risk improves from 0.082 to 0.103, indicating a significant enhancement in the explanatory power of the models. The coefficient of the effect of green credit on bank risk is significant at the 5% level, indicating that green credit can reduce

Table 3. Baseline regression results

Model	(1)	(2)	(3)	(4)
Variable	RISK	RISK	RISK	RISK
<i>GREEN</i>	0.921***	0.808***	0.706***	0.688**
	(4.034)	(3.136)	(2.672)	(2.548)
<i>NGDP</i>		0.040	0.013	0.023
		(0.259)	(0.081)	(0.142)
<i>SIZE</i>		0.005	0.008	0.009
		(0.958)	(1.525)	(1.630)
<i>LDR</i>			-0.001	-0.001
			(-1.613)	(-1.447)
<i>NIM</i>				0.012
				(0.546)
<i>NI</i>				-0.000
				(-0.249)
<i>_cons</i>	9.106***	8.979***	8.959***	8.892***
	(916.057)	(69.132)	(68.965)	(57.008)
N	185	185	185	185
R ²	0.082	0.087	0.100	0.103
F	16.271	5.733	4.988	3.402
p	0.000	0.001	0.001	0.003

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

bank risk and that this effect is influenced by the macro environment and the bank’s own operating conditions, which supports hypothesis 1.

It should be noted that in order to ensure the accuracy and reliability of the regression results, the fixed-effects model was finally selected for regression analysis in this paper on the basis of the test results of the F-statistic test and the Hausman test.

4.3 Robustness Test

In this section, three approaches were used to test the robustness of the model. First, we changed the bank risk indicator to $Z\text{-score}=(ROA+CAR)/ROA_SD$, where the capital adequacy ratio CAR was represented by the capital-to-asset ratio ETA , resulting in a new bank risk indicator $Z\text{-score}2$ (Dräger et al., 2021). Second, we add the control variable ROA to provide a more comprehensive consideration of bank risk. Finally, we chose a sample size from 2018-2021 for the regressions. Table 4 shows the regression results of the impact of green credit on bank risk under different methods. From model (1) to model (3), the coefficients of the impact of bank credit on bank risk are 0.307, 0.638, and 0.529, respectively, all at the 10% level of significance. This indicates that the findings on green credit reducing bank risk are robust.

Table 4. Robustness test regression results

Model	(1)	(2)	(3)
Variable	Substitution of Explanatory Variables	Add Control Variables	Reduced Sample Size
<i>GREEN</i>	0.307	0.638**	0.529*
	(0.978)	(2.418)	(1.804)
<i>SIZE</i>	-0.009	0.006	0.015**
	(-1.388)	(1.140)	(2.537)
<i>NIM</i>	0.079***	-0.015	0.022
	(3.044)	(-0.627)	(0.850)
<i>LDR</i>	0.004***	-0.000	-0.002***
	(6.271)	(-0.655)	(-2.671)
<i>NI</i>	0.001	-0.001	-0.000
	(1.131)	(-1.137)	(-0.294)
<i>NGDP</i>	0.131	-0.045	0.102
	(0.710)	(-0.291)	(0.655)
<i>ROA</i>		16.622***	
		(3.235)	
<i>_cons</i>	3.739***	8.891***	8.787***
	(20.607)	(58.499)	(54.155)
<i>N</i>	185	185	148
<i>R</i> ²	0.248	0.153	0.160
<i>F</i>	9.807	4.565	4.478
<i>p</i>	0.000	0.000	0.000

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

4.4 Dynamic Test

In terms of the significance of the coefficients, the coefficient of green credit and commercial bank risk for lag 1 is 0.591 (significant at the 5% level). The coefficient of green credit and commercial bank risk for lag 2 is 0.862 (significant at the 5% level), and the coefficient of green credit and commercial bank risk for lag 3 is 0.880 (significant at the 5% level). This indicates that commercial banks are more effective in reducing bank risk after one to two years. The coefficient of green credit at lag 3 confirms Hypothesis 2.

5 FURTHER ANALYSES

5.1 Mechanism Assumptions

This paper argues that the core mechanism through which green credit affects commercial banks' risk-taking is banks' leverage risk.

From the perspective of commercial banks, the government's policy support for the green credit industry increases the demand for green financing. This leads banks to develop new green credit

Table 5. Dynamic test results

Model	(1)	(2)	(3)
Variable	RISK	RISK	RISK
<i>GREEN1</i>	0.591**		
	(2.000)		
<i>GREEN2</i>		0.862**	
		(2.562)	
<i>GREEN3</i>			0.880**
			(2.192)
<i>SIZE</i>	0.014**	0.015**	0.018**
	(2.332)	(2.163)	(2.162)
<i>NIM</i>	0.026	-0.007	-0.032
	(1.004)	(-0.220)	(-0.917)
<i>LDR</i>	-0.002***	-0.002***	-0.002***
	(-2.948)	(-2.853)	(-2.946)
<i>NI</i>	-0.000	-0.000	0.001
	(-0.118)	(-0.069)	(0.729)
<i>NGDP</i>	0.142	0.125	-2.018**
	(0.908)	(0.816)	(-2.337)
<i>_cons</i>	8.716***	8.855***	8.157***
	(45.129)	(40.391)	(19.782)
N	148	111	74
R ²	0.183	0.268	0.405
F	4.475	5.375	6.409
p	0.000	0.000	0.000

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

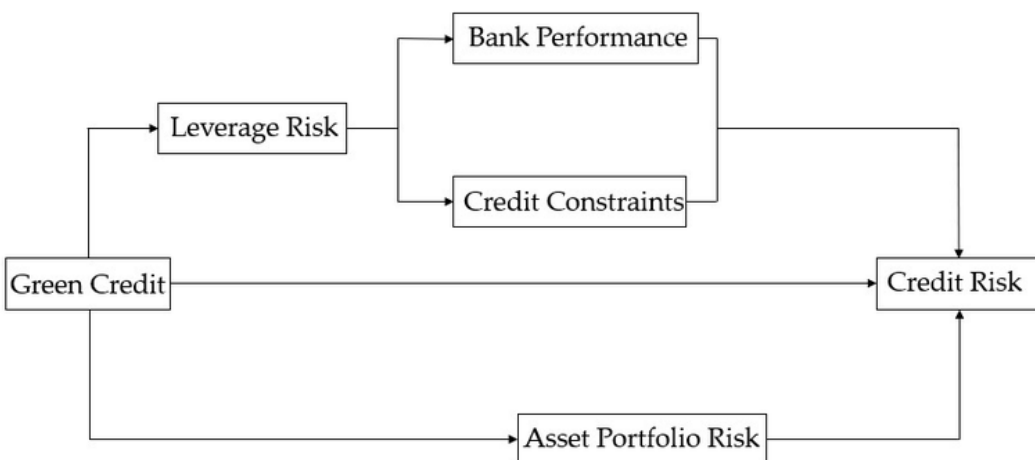
businesses such as carbon asset collateral financing and contract energy management financing (Ashraf et al., 2020). Such businesses help improve banks' competitiveness, which in turn reduces their financing costs and thus triggers them to improve their performance by increasing leverage. The increased leverage ratio will have a positive impact on banks' technical efficiency and return on assets. At the same time, it will reduce their NPL (Non-performing Loan) and loan-to-deposit ratio, enhancing their ability to resist risks and facilitating stable operation (Zhang, 2022; Yuan, 2023).

From the perspective of enterprises, on the one hand, banks and financial institutions promote green credit based on the policy perspective of environmental protection and sustainable social development, using financial leverage to achieve environmental benefits by strengthening enterprises' awareness of environmental protection and by promoting enterprises' energy-saving, emission reduction, and technological upgrading (Haohong, 2021; Hemmelskamp, 1997). This effort also allows commercial banks to avoid the indirect risk of being unable to repay loans or of being penalized for environmental pollution projects because of their violating environmental protection laws by lending to the enterprises themselves. On the other hand, green credit policy can make banks, as the core of the financial systems, follow the corresponding industrial policy through the use of interest rate leverage to guide the flow of credit funds to low-carbon projects, environmental protection, green cleaning, and other projects. Banks can also impose certain credit constraints on high-pollution, high energy-consuming project industries (Hong et al., 2021; Xiang et al., 2022; Shi et al., 2022). Once a certain leveraging effect is established, more resources will be injected into the green production field, accelerating the improvement of investment and financing behavior among enterprises, promoting the exit or transformation of "two high and one leftover" enterprises, stimulating the transformation of polluting enterprises while driving the development of green industries such as green cleaning and environmental protection, and enriching the bank credit model. These developments will also enrich the bank credit model, improve bank credit quality, improve liquidity, and, in turn, reduce bank credit risk (Abbas et al., 2019; Naili & Lahrichi, 2022). On the basis of the above analysis, Hypothesis 3 is proposed:

Hypothesis 3. *Financial leverage plays a mediating role in the relationship between green credit and credit risk.*

The mechanism hypotheses above are introduced into mechanism design; the framework is shown in Figure 2.

Figure 2. Mechanism design



5.2 Model Setting

In order to test the intrinsic mechanisms and channels of action of the effect of green credit on bank risk, the following econometric model is set up in this paper as shown in Eq. 3 and Eq. 4:

$$RROA_{it} = \beta_0 + \beta_1 GREEN_{it} + \beta_2 SIZE_{it} + \beta_3 NIM_{it} + \beta_4 LDR_{it} + \beta_5 NI + \beta_6 NGDP_{it} + \delta_i + \lambda_t + \varepsilon_{it} \quad (3)$$

$$RCAR_{it} = \beta_0 + \beta_1 GREEN_{it} + \beta_2 SIZE_{it} + \beta_3 NIM_{it} + \beta_4 LDR_{it} + \beta_5 NI + \beta_6 NGDP_{it} + \delta_i + \lambda_t + \varepsilon_{it} \quad (4)$$

To further analyze the impact path of green credit on bank risk, with reference to the study of Li et al. (2014), this paper examines the Z-value in two separate components, namely, asset portfolio risk (RISK2) and leverage risk (RISK3), whose subdivided components are calculated as in Eq.5 and Eq.6:

$$RISK2 = \frac{ROA}{ROA_SD} \quad (5)$$

$$RISK2 = \frac{ROA}{ROA_SD} \quad (6)$$

where *RISK2* is the rate of return after bank risk adjustment, reflecting the ability of banks to increase risks with profit increase. *RISK3* reflects the ability to respond to the risk of bank stock capital. In the measurement equation, *RROA_{it}* and *RCAR_{it}* are the explanatory variables for “bank risk-taking”; *GREEN_{it}* is the explanatory variable for “green credit”; *SIZE_{it}*, etc., are a series of control variables. δ_i and λ_t denote individual and year effects, respectively, to avoid the influence of other unaccounted individual characteristics and time-varying factors on the accuracy of regression results. ε_{it} is a random error term. *i* and *t* denote sample banks and time, respectively.

5.3 Discussion of Mechanism Test Results

The test results of the green credit on the risk influence mechanism of commercial banks are shown in Table 6. Among them, the model (1) (2) is the rate of yields and leverage risks after bank risk adjustment, respectively. The estimated result of model (1) is 0.369, indicating that the estimated coefficient of the impact of green credit on bank risk-adjusted return is positive but insignificant. The estimated result of model (2) is 0.585, which reveals that the estimated coefficient of the one-period lag of green credit and leverage risk is significant at the 5% level. This finding suggests that reducing leverage risk will reduce bank risk more significantly than diversifying asset allocation, and there are obvious characteristics of dynamic enhancement.

In summary, by decomposing the Z-values, it can be found that the increase in the share of green credit weakens bank insolvency risk by reducing bank leverage risk and asset portfolio risk. The time-lagged impact of green credit on bank insolvency risk originates mainly from leverage risk, and the dynamic impact of green credit on bank insolvency risk is more evident in leverage risk.

6 FEDERATED LEARNING-BASED CREDIT RISK CONTROL

6.1 Overview of Federated Learning

Federated learning is a distributed machine learning model that aims to address the challenges of user privacy security and data silos in machine learning. It originated from Google’s proposal in 2016 to collaboratively train Gboard system input prediction models without centralizing user data. The key difference between federated learning and traditional machine learning is that federated learning avoids uploading large amounts of data owned by different parties to a central server (Gu et al., 2022;

Table 6. Mechanism test results

Model	(1)	(2)
Variable	RISK	RISK
GREEN	0.369	0.585**
	(0.757)	(2.157)
SIZE	0.017	0.011*
	(1.617)	(1.957)
NIM	0.190***	0.002
	(4.704)	(0.070)
LDR	-0.003***	-0.001
	(-2.953)	(-1.642)
NI	0.007***	-0.001
	(3.796)	(-0.763)
NGDP	0.535*	0.018
	(1.893)	(0.115)
_cons	0.699**	9.008***
	(2.392)	(55.399)
N	185	185
R ²	0.196	0.128
F	6.148	3.711
p	0.000	0.001

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

Li et al., 2022; Kang et al., 2019; Wu et al., 2020; Yang et al., 2020). Instead, federated learning trains models by sending machine learning algorithms to individual parties and coordinating shared model training through a central server.

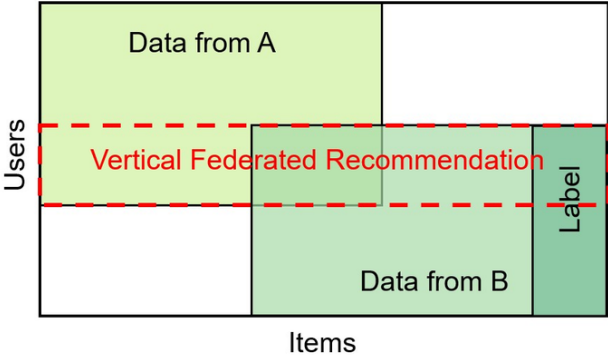
Federated learning can be divided into three categories based on the relationship between the various data silos in the model: vertical federated learning, horizontal federated learning, and federated migration learning.

6.2 Bank Credit Risk Control Based on Vertical Federated Learning

Vertical federated learning is characterized by the same sample IDs, but different data features (Yang et al., 2019). To illustrate this, let's consider two data silos represented by rectangles (D). The rows of the rectangle correspond to object IDs (i), and the columns correspond to different features of the object ID (x). The label (y) of each object ID is predicted on the basis of its features. The range of the training data is shown by the red dashed line in Figure 3. The formal definition of the vertical federated learning model is given by Eq (7).

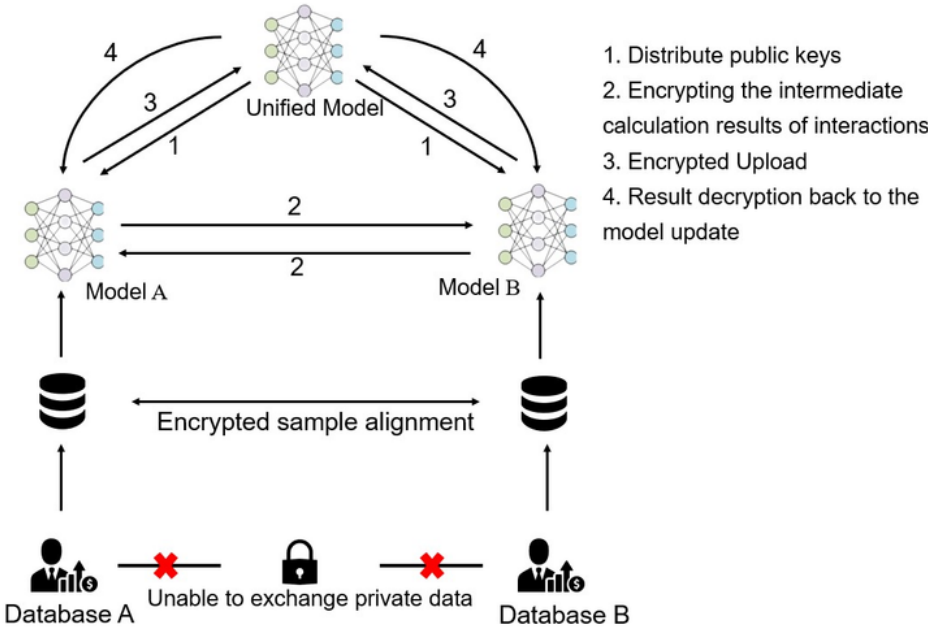
$$\begin{cases} x_i \neq x_j \\ y_i \neq y_j \quad \forall D_i, D_j, i \neq j \\ i_i \neq i_j \end{cases} \quad (7)$$

Figure 3. Vertical federated learning model training data



Vertical federated learning requires the use of encryption for object ID alignment to ensure that non-overlapping object information in each party’s data is not leaked. The overlapping part of the data is used for encryption training. The training process involves several steps (Phong et al., 2018; Zhang et al., 2023; Li et al., 2022; Xu et al., 2020). First, a server (C) is initialized and encrypted with user information, and participants A and B initialize their model parameters. Next, server C distributes encrypted user information to participants A and B. Participants update their model parameters by decrypting user information and calculating loss on the basis of local data. The two parties then calculate the gradient of user information and encrypt the result to server C. Finally, server C passes the decrypted gradients and losses back to participants A and B to update their respective model parameters. This process repeats for several iterations until the model converges. Figure 4 visualizes the training process, and the current regression model with homomorphic encryption is used as an example to specify the training process of longitudinal federated learning in this paper.

Figure 4. Vertical federated learning model training process



The federated learning model participants are denoted by A and B, with their respective data sets being represented as $\{x_i^A\}_{i \in D_A}$, $\{x_i^B, y_i\}_{i \in D_B}$ and their model parameters as θ_A, θ_B . The regularization parameter is γ , and the learning rate of the model is η . The optimization objective can be expressed as follows:

$$\min_{\theta_A, \theta_B} \sum_i \|\theta_A x_i^A + \theta_B x_i^B - y_i\|^2 + \frac{\gamma}{2} (\|\theta_A\|^2 + \|\theta_B\|^2) \quad (8)$$

Assuming homomorphic encryption is represented by $[\]$, and setting $v_i^A = \theta_A x_i^A, v_i^B = \theta_B x_i^B$, the encryption loss can be expressed as:

$$[\xi] = \left[\sum_i \|v_i^A + v_i^B - y_i\|^2 + \frac{\gamma}{2} (\|\theta_A\|^2 + \|\theta_B\|^2) \right] \quad (9)$$

Set the loss function of the participants respectively, as shown in the following formula:

$$\begin{aligned} [\xi_A] &= \left[\sum_i \left((v_i^A)^2 \right) + \frac{\gamma}{2} \theta_A^2 \right] \\ [\xi_B] &= \left[\sum_i \left((v_i^B - y_i)^2 \right) + \frac{\gamma}{2} \theta_B^2 \right] \\ [\xi_{AB}] &= 2 \sum_i \left(v_i^A (v_i^B - y_i) \right) \\ [\xi] &= [\xi_A] + [\xi_B] + [\xi_{AB}] \end{aligned} \quad (10)$$

Set to $[d_i] = [v_i^A] + [v_i^B - y_i]$, then the gradient can be expressed as:

$$\left[\frac{\partial \xi}{\partial \theta_A} \right] = \sum_i [d_i] x_i^A + [\gamma \theta_A] \quad (11)$$

$$\left[\frac{\partial \xi}{\partial \theta_B} \right] = \sum_i [d_i] x_i^B + [\gamma \theta_B] \quad (12)$$

6.3 Application Practice of Federated Learning in Bank Credit Risk Control

This paper presents a federated learning model that utilizes seven indicators, such as the balance of green credit business and transaction information data from commercial banks. Financial institutions, such as banks and consumer finance companies, integrate their own accumulated corporate green financial behavior information with external data related to the company to establish an accurate model (Wu et al., 2020; Das et al., 2022). The risk control model aims to solve problems such as white accounts in credit investigation and green enterprise loan difficulties caused by a lack of effective data, thereby effectively improving the credit risk control level of banks (Sattler et al., 2021; Zhang et al., 2021).

Data is a crucial component of federated learning modeling. In this paper, we aim to establish a precise risk control model based on green credit. During the model-building process, we carefully

selected common indicators and data calibers for data development, based on the actual situation of data collection. Table 7 presents the overall standard framework used.

Using federated learning technology, we can encrypt and fuse data to build federated models. After training, optimizing, and debugging the model, we obtained the following results:

- (1) By fusing data from multiple banks and utilizing federated learning, we were able to fit a final model with a true positive rate of 1 while still protecting user privacy. This demonstrates the effectiveness of the federated learning approach.
- (2) While the joint model’s performance index dropped slightly compared to the index obtained using a single bank’s data, it still remained at a high level of stability. Furthermore, the joint model benefitted from the access to data from multiple cooperating banks, resulting in more comprehensive green credit information being disclosed. The federated learning training process also contributed to the individual models’ improvement, ultimately enhancing the overall robustness of the model.

7 CONCLUSION AND POLICY PROPOSAL

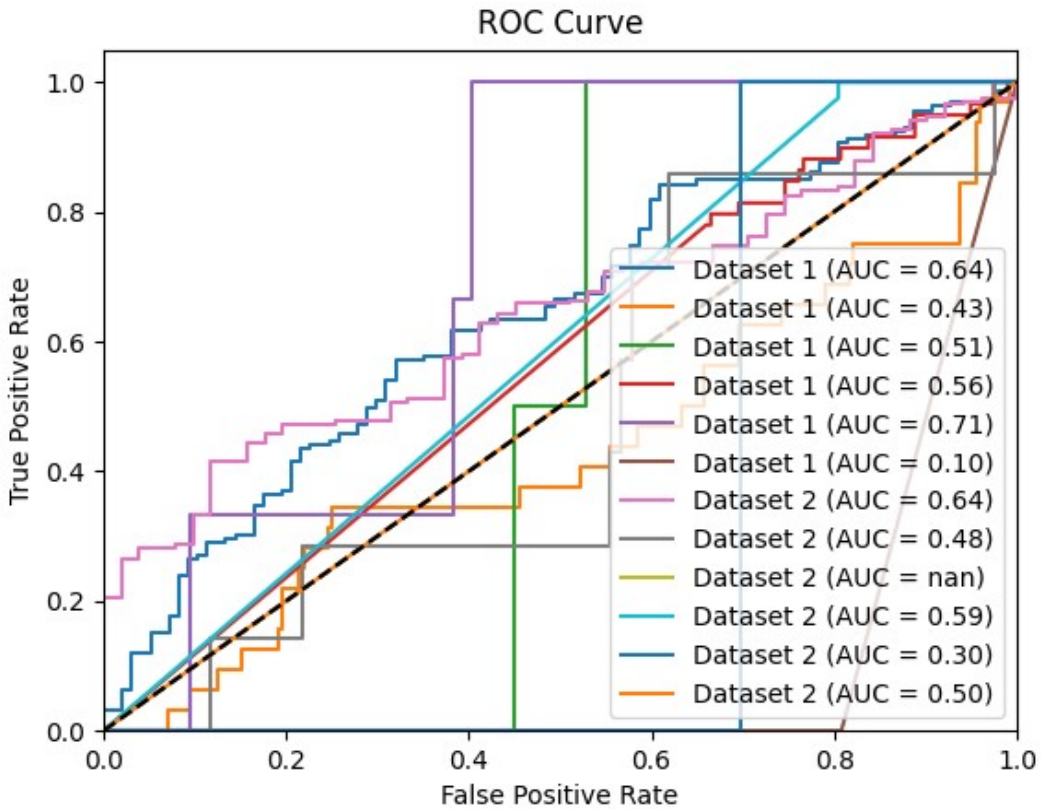
7.1 Conclusions and Prospects

This paper empirically examines the relationship between green loans and banks’ risk management using data from 26 listed commercial banks in China during the period from 2015 to 2021. The results show that increasing the proportion of green loans can strengthen banks’ risk management and improve their future risk appetite. The risk mitigation effect of this policy on banks increases over time. In examining the mechanism of action, we find that the risk-mitigating effect of green loans results from the financial leverage properties of banks themselves; i.e., green loans improve banks’ ability to manage risk by increasing funding levels and improving their liquidity. Finally, this paper integrates seven key indicators, including individual commercial banks’ balance sheet and transaction data on green loans, through vertical federated learning. When these data are merged with information on corporate green financial behavior and relevant external data, an accurate risk control model is built. This model aims to address the challenges posed by the information asymmetry between banks and firms, as well as the difficulties involved in lending to white households and green firms due to the lack of reliable data. The results presented in

Table 7. Data standards framework for federated learning

Indicator Category	Indicator Content
Trading Information	Transaction subject, date, province
Green Credit	The average expenditure amount and growth rate in the past three months, and the destination of funds
Channel Preference	Mobile banking transaction amount, Internet banking transaction amount, counter transaction amount, self-service equipment transaction amount
Customer Base Properties	User name, IP address, size
Past Investment History	Investment age, number and total amount of green credit-related financial products purchased in the past year
Equipment	The number of devices, the number of IPs in the last x days, the city to which the IPs belonged in the last x days
Trading Time Preference	The number of sensitive time transactions in the past x days, the number of normal time breakpoint transactions in the past x days

Figure 5. Federated learning model training results



this paper provide valuable empirical evidence for improving banks' credit risk management practices. The fusion of federated learning and green credit not only innovates the design of a new artificial intelligence implementation mode, more importantly, federated learning creates a new paradigm for machine learning tripartite data protection; more importantly, federated learning creates a new paradigm of data protection in machine learning for three parties: enterprises, commercial banks, and audit institutions. In this new framework, when commercial banks audit of green credit enterprises, they do not have to deal with many aspects of a variety of different customer credit data, avoiding the inability to provide the corresponding green credit services because of the unavailability of key data banks, thus reducing the risk associated with green credit. At the same time, this study provides a new perspective for the application of artificial intelligence technology in the financial industry. Although federated learning has great appeal in solving the problem of data privacy and sharing, it is still not ready to be widely adopted in the real scenario of bank credit scoring because of insufficient incentives for participants, the need to improve the efficiency of the system, and the lack of a large amount of data support. Moreover, the sample for this study consists mainly of listed commercial banks. Regardless of the scale of green credit, the strength of political financial support and the application of the federal learning model for credit risk prevention and awareness control have obvious advantages over unlisted small and medium-sized commercial banks, which lack financial support and a complete credit assessment system.

7.2 Policy Proposal

On the basis of the above findings, the following policy implications can be proposed.

- Improve Green Credit Related Laws and Regulatory System

A sound legal system is a prerequisite for commercial banks to implement green credit business. The current foundation of green finance development is weak, the level of legislation related to green finance is still at a low level, and there are still major defects in related laws and regulations. Additionally, the definition and punishment of illegal acts, such as information fraud, are not strong enough. At the same time, because of the lack of a clear definition of the positive and negative externalities of the project, the government and enterprises lack the incentive to actively participate in environmental protection and energy conservation. Therefore, the legislative department should establish a restraint mechanism to clearly define illegal and unlawful behaviors in green credit and formulate strict punitive measures for different subjects, with social supervision and reporting to accelerate the pace of establishing a good green credit market environment.

- Improve the Information Disclosure Mechanism

The government plays a crucial role in promoting the development of green industries and enhancing the level of bank credit risk control. To achieve these goals, it should improve the environmental information disclosure system and mandate companies to disclose their environmental protection information in a timely and accurate manner. Furthermore, government departments should investigate companies' financing applications and guide loan funds toward financial companies that meet environmental protection requirements. Information exchange and risk monitoring should be strengthened throughout the lending process, and the environmental impact evaluation system associated with the financing of enterprise projects should be improved.

Establishing an environmental information disclosure system can also help screen out companies and projects that do not meet the requirements for credit loans. The government can use financial means to subsidize green industries, which have long investment cycles and limited development due to the lack of initial investment and lagging returns (Wang et al., 2019). Banks can use federated learning to establish green credit risk assessment models, combining external institutions' highly correlated credit data with their own data to provide personalized loan solutions for green enterprises.

With the government's support, green industries can improve their credit data in all dimensions, leading to inclusive finance and improved bank credit risk control. The government can also draw on foreign experience in subsidizing environmental costs to provide appropriate financial subsidies to green industries. By doing so, we can achieve the dual goals of promoting economic development and protecting the environment (Li et al., 2020; Lim et al., 2020).

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COMPETING INTERESTS

The authors of this publication declare there are no competing interests.

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