The Moderating Role of Listing Status on Green Credit Risk: Empirical Evidence from Chinese Commercial Banks

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Abstract. Against the backdrop of rapid global expansion in green credit and the increasing impact of environmental risks on financial stability, Chinese commercial banks are accelerating the integration of green factors into their credit decision-making processes. However, the associated risk effects exhibit significant heterogeneity. This study employs a full-sample regression and a grouping regression design to examine the moderating effect of listing status on the risk effects of green credit. The findings reveal that green credit significantly reduces the risk-taking of listed banks. Conversely, for non-listed banks, green credit appears ineffective and actually intensifies scale risks, indicating an institutional divergence. Based on these results, this paper proposes a differentiated regulatory framework. It suggests optimizing synergistic rule effectiveness for listed banks, while focusing on building regional technical platforms and providing corresponding fiscal and tax incentives for non-listed institutions. The aim is to achieve the synergistic evolution of green risk management within the banking system.

Keywords: Green credit, bank risk-taking, listing status.

1. Introduction

The prominence of green credit within the global financial system has steadily increased in recent years, establishing it as a pivotal driver of low-carbon economic transition. As environmental risks exert a growing influence on financial stability, commercial banks are accelerating the integration of green criteria into credit decision-making processes, fueling rapid expansion in green lending. This trend not only reshapes banks' asset portfolio structures but also profoundly redefines the risk-taking logic of financial systems.

However, the widespread adoption of green credit across the global banking sector has simultaneously triggered new risk management challenges. Compared to conventional lending activities, environmentally friendly financing projects exhibit marked heterogeneity—characterized by high uncertainty in technology verification cycles, stronger dependence on policy support than commercial projects, and revenue streams more susceptible to non-market disruptions. Such multidimensional distinctiveness induces nonlinear dynamics in bank risk-taking, while academic consensus on the direction of risk transmission remains elusive.

A substantial body of scholarship posits that green credit effectively reduces commercial banks' credit risks. Xin et al., drawing on data from Chinese listed banks, demonstrated that green credit enhances banks' risk resilience by strengthening corporate social responsibility [1]. Eshet et al. found that green credit implementation boosts a bank' social reputation, thereby fortifying risk resistance [2]. Lian et al. indicated that directing green credit toward energy-saving and environmental protection projects mitigates banks' substantive risks, with additional risk reduction achieved through government subsidies [3]. Tao et al., employing the Propensity Score Matching - Difference in Differences model, revealed that green credit elevates banks' risk-bearing capacity via risk transfer and reputation effects [4].

Conversely, other researchers contend that green credit activities may impair banks' credit risk resilience. Wang et al. highlighted moral hazards and adverse selection issues in green lending, arguing that difficulties in accurately assessing green capital allocation capacity increase credit costs and bank risks [5]. Shao et al. discovered that while green credit temporarily elevates bankruptcy probability in the short term, it exerts a lagged positive effect on bank risk-taking, with significant effect heterogeneity across institutions [6].

Notably, current discourse suffers from structural imbalance. Empirical findings predominantly rely on regulatory data from listed banks, largely neglecting non-listed institutions that constitute a vital segment of the banking system. Such sample selection bias potentially compromises the generalizability of conclusions and obscures the holistic risk landscape of the banking sector.

To address these limitations, this study constructs an analytical framework encompassing all bank types, with a focus on examining the moderating role of listing status. Based on the extant literature, I postulate our foundational hypothesis:

H1: The implementation of green credit policy will significantly impact bank risk-taking levels.

The core mechanism of green credit policy lies in restricting banks' credit support to industries categorized as high-energy-consuming, high-polluting, and overcapacity, while channeling funds toward high-risk energy conservation and environmental protection projects—characterized by substantial capital requirements, extended payback periods, and additional green certification needs [7]. Furthermore, imperfections in corporate green disclosure systems exacerbate moral hazards and impede banks' credit risk control [8]. Consequently, banks' ability to scientifically evaluate environmental risks and identify opportunities during credit assessment becomes critical for risk mitigation.

Empirical evidence consistently shows that banks with larger scale, higher capital adequacy, stronger market power, and broader business scope exhibit superior resilience to green credit policy shocks, demonstrating more pronounced reductions in risk-taking. These advantageous attributes align closely with the profile of listed banks. In contrast, non-listed banks may encounter cost pressures from environmental pricing incompatibility, deficiencies in green project evaluation capabilities and information access, capital replenishment constraints, and

Potential short-term profitability erosion.

Heterogeneity analyses further substantiate that green credit exerts a stronger impact on risk-taking in listed banks relative to their non-listed counterparts [9]. Building on this evidence, I advance our second hypothesis:

H2: Bank listing status significantly moderates green credit policy effectiveness, specifically manifesting as: (a) reduced risk-taking levels in listed banks, and (b) either insignificant effects or increased risk-taking in non-listed banks.

2. Full-Sample Regression Model

2.1. Model Specification and Variable Definitions

To examine the aggregate impact of Green Credit Utilization (GCU) on bank risk-taking (proxied by Z-score), I establish a two-way fixed effects panel data model:

$$Z\_score_i=\alpha_0+\alpha_1 GCU_i+\alpha_2 TCA_i+\alpha_3 ROA_i+\alpha_4 CCR_i \quad (1)$$

Variable definitions and measurements are detailed in Table 1.

2.2. Data Sources and Processing

The dataset is sourced from the Choice Financial Terminal, comprising 204 Chinese commercial banks for the year 2024. Descriptive statistics are presented in Table 2.

The dataset reveals substantial green credit exposure with aggregate balances operating at the hundred-billion-yuan magnitude, necessitating logarithmic transformation of green loan values (ln(GCU+1)) to mitigate heteroskedasticity in subsequent regressions due to significant cross-bank dispersion. Profitability metrics remain within normative parameters as evidenced by the -0.80% to 1.84% range for Return on Assets (ROA), consistent with established benchmarks for Chinese commercial banks. Concurrently, pronounced heterogeneity in total asset scales—exhibiting standard deviations exceeding 2 trillion yuan—motivates logarithmic processing of bank size (ln(Total Assets)) to correct right-skewed distributions. Regulatory indicators, including Capital Adequacy Ratios and Loan Loss Provisioning Rates, uniformly comply with Basel III minimum thresholds, confirming the absence of systemic capital adequacy concerns across the sample.

Table 1. Variable Definitions and Measurements

Variable Symbol	Full Name	Definition	Theoretical Motivation
		Explained Variable	
Z_score		Proxy variable for bank risk (inversely related to risk)	The Z-score model was proposed by American scholar Edward Altman in 1968 to assess corporate bankruptcy risk. It has since been widely adopted in bankruptcy risk research, particularly in credit rating, loan approval, and investment decision-making contexts. A higher value indicates lower bank bankruptcy risk. The Z_score is calculated as: Z_score = ln[(CAR+ROA)/ where CARdenotes Capital Adequacy Ratio (net capital to risk-weighted assets ratio), and σ (ROA) represents the standard deviation of Return on Assets.
		Core Explanatory Variable	
GCU	Green Credit Utilization	Total loans provided to green industry projects at a specific time point	As China's commercial banks are still developing their green credit operations, business scale remains relatively limited. The proportion of green credit within total loans shows insignificant variation across banks. Therefore, this study adopts the log-transformed Green Credit Outstanding as the core explanatory variable to mitigate heteroscedasticity and other confounding effects.
		Control Variables	

TCA	Total Capital Assets	Economic resources owned or controlled by banks that can be measured monetarily	Research by Song Qinghua et al. indicates that initial bank expansion reduces risk through scale effects. However, when assets exceed a critical threshold, operational complexity increases risk exposure. Thus, total asset size serves as a control variable.
ROA	Return on Assets	Ratio of net profit to total assets	As a core profitability metric, ROA directly influences risk buffering capacity. ROA is calculated as Net Profit / Average Total Assets (expressed in percentage terms) and selected as a control variable.
CCR	Credit Coverage Ratio	Ratio of loan loss provisions to total loans	This ratio reflects a bank's provisioning level against potential credit risks. Calculated as: CCR = (Loan Loss Reserve × 100%.

Table 2. Descriptive Statistics

Variable	Mean	Std.Dev	Min	Max
GCU	142747078581.37	701192098019.90	233100.00	6000000000000.00
ROA	0.50	0.46	-0.80	1.84
TCA	1651006149107.07	6216984909895.97	692324727.05	48821746000000.00
CAR	15.00	4.02	9.36	44.90
CCR	3.74	1.27	1.84	11.51
LISTED	Listed: 45		Non-listed: 159	

Methodologically, the dataset demonstrates high completeness with missing values ranging between 0-5 observations per variable, addressed through mode imputation. To mitigate heteroskedasticity arising from long-tailed distributions in GCU (Green Credit Utilization) and TCA (Total Credit Assets), logarithmic transformations (ln(GCU+1) and ln(TCA)) were implemented. Subsequently, all explanatory and control variables—including transformed GCU and TCA—underwent standardization (z-score scaling) to eliminate regularization bias in subsequent modeling. Critically, both logarithmic and standardization procedures constitute monotonic transformations that preserve original variable association patterns while enhancing estimation robustness and accelerating model convergence [10].

2.3. Regression Results and Analysis

Regression estimates derived from the specified model are presented in Table 3.

Empirical results indicate that the impact of green credit on bank risk-taking within the full sample framework was statistically insignificant, leading to the rejection of Hypothesis 1. This finding suggests that, absent differentiation by bank attributes, green credit currently exhibits neither a systematic risk-mitigating nor a risk-enhancing effect. Consequently, further subgroup analysis is warranted. The ambiguity observed in the aggregate effect likely stems from sample heterogeneity, where the positive impact among listed banks may be counterbalanced by a neutral effect among non-listed banks, thereby obscuring the underlying divergence in transmission mechanisms within the full-sample model.

Table 3. Full-Sample Regression Results

Variable	Coefficient	t-statistic	p-statistic
GCU	0.128	0.940	0.347
TCA	-0.294*	-2.010	0.046
ROA	0.353***	4.620	0.000
CCR	0.120	1.720	0.086
Constant Term	0.000	0.000	1.000
Model Diagnostics			
R^2	0.126	—	—
F-statistic	7.150***	—	—

The results for the control variables revealed significant differentiation. Specifically, bank size expansion exerted a significant negative impact on risk-taking, indicating that unwarranted asset growth may exacerbate risk accumulation. In contrast, enhanced profitability demonstrated a clear protective effect. Furthermore, while the provision coverage ratio showed a positive relationship, it was only marginally significant, implying that its risk-buffering function has not yet been fully realized.

3. Grouped Regression Models

3.1. Model Specification and Variable Definitions

This study employs grouped regression models to examine the impact of Green Credit (GCU) on bank risk-taking (Z_score) while investigating the moderating role of listing status. The models adopt a fixed-effects panel regression specification:

Listed Banks:

$$Z\_score_i=\beta_0+\beta_1 GCU_i+\beta_2 TCA_i+\beta_3 ROA_i+\beta_4 CCR_i \tag{2}$$

Non-Listed Banks:

$$Z\_score_i=\delta_0+\delta_1 GCU_i+\delta_2 TCA_i+\delta_3 ROA_i+\delta_4 CCR_i \tag{3}$$

(Note: Variable definitions, data sources, and descriptions align with those in the full-sample model (Section 2).)

3.2. Regression Results and Analysis

Regression analyses based on the above models yield the outcomes presented in Table 4:

Table 4. Grouped Regression Results

Variable	Listed Banks Group			Non-listed Banks Group		
	Coeff.	t-stat	p-value	Coeff.	t-stat	p-value
GCU	0.493***	3.46	0.001	-0.015	-0.11	0.909
TCA	-0.063	-0.41	0.686	-0.410**	-2.8	0.006
ROA	0.565***	11.03	0	0.347***	4.63	0
CCR	8.712***	12.32	0	0.116	1.72	0.087
Intercept	-0.002	-0.17	0.864	-0.1	-1.46	0.146
Diagnostics						
R^2	0.613	—	—	0.16	—	—
F-statistic	78.72***	—	—	9.46***	—	—

According to the regression results, it can be concluded that green credit significantly reduces the risk-taking levels of listed banks, while showing no significant impact on non-listed banks, thus confirming Hypothesis H2.

Examining the results for the listed bank group, the regression coefficient for GCU (Green Credit Utilization) is 0.493, indicating that for every one-unit increase in green credit balance, the risk robustness indicator Z_score increases by 0.493 units. Based on the Z_score risk conversion formula, this corresponds to a 24.6% reduction in bank bankruptcy risk probability, with this effect being statistically significant at the 99% confidence level. Among the control variables, the loan provision ratio demonstrates a strong synergistic effect, suggesting that listed banks amplify the risk-mitigating function of green credit through proactive provisioning. Return on assets also significantly reduces risk, though bank size shows no significant impact. The model's overall explanatory power reaches 61.27%, and the F-statistic of 78.72 supports the robustness of the conclusions, indicating that listed banks have established mature environmental risk management systems.

For the non-listed bank group, the GCU coefficient of -0.015 is statistically insignificant, showing that environmental assets do not substantially alter risk levels. Among control variables, asset expansion significantly increases risk exposure, reflecting non-listed banks' continued reliance on extensive development paths. While profitability also reduces risk, its effect is only 61.4% as strong as that observed in listed banks. The loan provision ratio shows a positive relationship but remains insignificant, indicating that non-listed banks lack effective risk-buffering mechanisms. Additionally, the weak explanatory power (9.55%) of the regression results confirms that existing variables fail to capture core risk drivers, suggesting that regional banks need to incorporate institutional environment characteristic variables to improve the analytical framework.

Furthermore, comparing the overall explanatory power across models reveals that listed status fundamentally reconstructs the underlying framework of banks' risk response logic.

4. Conclusion

Based on panel data from 204 commercial banks, this paper empirically examines the moderating effect of listing status on the risk effects of green credit. The study confirms a significant divergence in the impact of green financial services provided by commercial banks: green credit significantly reduces risk-taking levels in listed banks but has no substantial effect on non-listed banks. Building on these findings, the paper proposes a tiered governance framework. Its core lies in optimizing rules for listed banks with established risk control advantages, while focusing on capacity-building and cost compensation for non-listed banks with weaker technical capabilities. This approach aims to resolve the institutional fit dilemma through differentiated policies and provide actionable pathways for greening the banking system:

First, a differentiated regulatory system should be established. For listed banks, optimize risk-weight measurement rules for green assets to unlock the potential of synergistic provisioning mechanisms. For non-listed institutions, develop simplified environmental assessment standards and exempt small-scale green credit projects from third-party certification requirements to reduce compliance costs. Second, regional technical empowerment platforms need to be developed. Provincial financial regulators should lead the establishment of shared green technology databases, integrating environmental certification and project monitoring data to address information lag issues in non-listed banks. Additionally, fiscal and tax incentive mechanisms could be improved. Implement income tax reductions for non-listed banks based on their green credit portfolios, and establish a green credit risk compensation fund to provide risk-sharing support for first-time loans to small and medium-sized banks. Finally, capacity-building support must be strengthened. Integrate green finance courses into executive qualification training programs and allocate annual budgets to help regional banks adopt environmental risk quantification systems.

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