The Impact of Green Credit on Industrial Structure Upgrading: Evidence from Chinese Prefecture-Level Cities

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Abstract. This study utilizes 2005-2022 panel data from 225 prefecture-level cities in China to construct a two-way fixed effects model. The empirical results show that green credit significantly advances industrial structure. Heterogeneity analysis indicates its effect is stronger in more developed regions than in less developed ones, and more pronounced in the eastern region than in the central and western regions. These findings offer guidance for crafting targeted policies and driving green transformation in developing economies.

Keywords: Green Credit, Industrial Structure Upgrading, Heterogeneity, Prefecture-Level City, Fixed-Effects Model.

1. Introduction

Against the accelerating global climate governance and sustainable development agendas, green finance drives low-carbon transition. China’s core policy instrument—green credit—redirects capital from polluting industries to green sectors via environmental risk assessment, making its efficacy a critical research focus [1-2].

China, the world's largest developing economy, is shifting toward a service-oriented model. This requires upgrading traditional industries while strengthening producer services. Under "dual carbon" goals, accelerated decarbonization of energy-intensive sectors and scaling renewables are crucial. This transformation enhances growth quality and builds a low-carbon industrial system for development-ecology synergy [3].

Existing literature explores green credit’s environmental and economic effects through multidimension. Environmentally, green credit picies suppress corporate carbon emissions and energy consumption intensity in high-pollution industries by incorporating environmental risks into lending frameworks [4-5]. Mechanisms such as alleviating financing constraints and incentivizing green innovation further drive green transitions and environmental investments in heavy-polluting firms [2][6]. Economically, green credit optimizes financial resource allocation and stimulates innovation, significantly boosting the share of non-agricultural industries and promoting industrial structure transformation [1][7]. By enhancing R&D investment and information disclosure quality, green credit also promotes green innovation and total factor productivity growth [8-9]. However, policy impacts exhibit regional heterogeneity: eastern regions leverage urbanization and market mechanisms synergistically, while central and western regions benefit from cross-regional financial resource allocation [10].

There are two limitations of existing studies. First, most existing studies focus on traditional financial metrics. For instance, Tan et al. employ traditional indicators like "asset-liability ratio" and "current ratio," which focus narrowly on financing constraints while overlooking green credit’s unique role in spurring technological innovation [4]. Similarly, Zhang et al. fail to distinguish green finance from traditional finance by using "economic performance", thereby obscuring green credit’s specific contributions to green growth [11]. Jia et al. prioritize "loan interest rates" as core variables, neglecting how technological innovation and policy implementation efficiency amplify the effects of green credit, resulting in superficial policy analyses. Second, insights into prefecture-level policy variations are constrained by data limitations [6]. Zheng et.al. analyze provincial panel data (2006–2019), identifying spatial spillover effects but overlooking municipal-level institutional differences in industrial catalog formulation and environmental information disclosure [11]. Wan et.al. utilize western provincial data to examine fintech's regional heterogeneity in green credit's carbon reduction efficacy, but provincial aggregates mask disparities in financial infrastructure across prefecture-level cities [5].

Compared with prior literature, this paper offers two marginal contributions. First, this paper studies the impact of green credit on industrial structure upgrading. Different from the one-way analysis of traditional financial indicators [11], this study incorporates the environmental and economic effects of green credit into a unified model, more comprehensively reveals the dual role of green credit in "environmental protection" and "industrial upgrading", and explores the effect differences caused by differences in the industrial foundation and policy implementation in different regions. Second, this paper relies on panel data from 225 prefecture-level cities in China spanning the period 2005–2022. Because the effect of green financial policy highly depends on the implementation of local governments and regional economic characteristics, this highlights the necessity of urban level research [12]. Thus, this paper explores the influence of green credit on industrial structure upgrading by constructing a two-way fixed effects model to control for individual and temporal variations. Furthermore, it conducts a deeper analysis of the heterogeneity in economic development levels and geographical locations.

Key findings of this paper demonstrate that green credit significantly promotes industrial structure upgrading. Heterogeneity analyses reveal stronger effects in developed regions and the eastern provinces, contrasting with weaker or insignificant impacts in less-developed and central/western areas. These results underscore the necessity of differentiated policies tailored to regional economic conditions and geographic contexts.

2. Data and model

2.1. Data

(1) Explained variable

Industrial structure upgrading (*isu*) denotes the systematic reallocation of productive resources from inefficient, resource-intensive sectors toward knowledge-based and environmentally sustainable activities. This transition—propelled by technological innovation, policy adaptation, and industrial symbiosis—shifts economic systems from factor-dependent paradigms toward innovation-driven value creation.

This study operationalizes *isu* as the proportion of tertiary industry value-added in regional GDP [13], a metric aligned with the "Tertiary Industry Dominance Hypothesis" [14] and widely adopted in comparative development studies. The tertiary sector's expanding share reflects advancements in service innovation, business process outsourcing, and digital economy integration—key markers of advanced industrial capabilities. The formula for industrial structure upgrading is expressed as follows:

$$isu = \frac{Y_3}{GDP} \tag{1}$$

Where Y_3 denotes the value added of the tertiary sector.

(2) Explanatory Variable

Green credit (*gc*) refers to financial institutional arrangements whereby financial institutions integrate environmental and social risks into lending decisions, guiding capital toward environmentally friendly industries and projects. Its core mechanism involves market-based tools—such as differentiated pricing and credit access restrictions—to internalize environmental externalities, thereby facilitating green structural transformation and sustainable development. The selection of green credit projects adheres strictly to the Green Industry Guidance Catalogue, mandating that projects fall within six designated green industry categories and comply with specific environmental technical standards. This study operationalizes *gc* as the ratio of green project credit volume to total credit volume in a prefecture-level city [15].

(3) Control Variables

This research selects the amount of green patent applications (*gpa*), government intervention (*gn*), urbanization level (*ul*), financial development (*fd*) and the degree of opening up (*ou*) as control variables [16-17]. The description of all variables selected in this paper is shown in Table 1.

Table 1 Brief description of variables

Variable type	Variable name	Variable symbol	Definition
Explanatory variable	Green credit	*gc*	Green credit balance of prefecture level cities/total credit balance of financial institutions in prefecture level cities
Explained variable	Industrial structure upgrading	*isu*	Added value of tertiary industry/GDP
Control variable	Green patent application	*gpa*	Logarithm the number of green patent applications
	Government intervention	*gn*	Local government general public budget expenditure/GDP
	Urbanization level	*ul*	Urban resident population/total resident population
	Financial development	*fd*	Loan balance of financial institutions at the end of the year/GDP
	Opening up	*ou*	Total import and export/GDP

(4) Data Processing

Employing panel data from 225 Chinese prefecture-level cities (2005-2022), this research sourced data chiefly from relevant China Statistical Yearbooks (Science & Technology, Finance, Agriculture, Industry, Tertiary), the National Bureau of Statistics Database, and official websites.

In this study, the linear interpolation filling method is used to deal with missing values. After the variable values are arranged from small to large, the extreme value of the data is processed by 1% tail reduction. By using the method of Z-score standardization, the data is standardized.

2.2. Data analysis

Descriptive statistical analysis

The descriptive statistics results are presented in Table 2. The average value of green credit ratio is 0.046 and the standard deviation is 0.017, indicating relatively stable green credit levels across 225 prefecture-level cities. The industrial structure upgrading index shows a mean of 0.398 and the standard deviation is 0.089, reflecting that the added value of the tertiary industry accounted for 39.8% of GDP on average during 2005–2022. This suggests China's economy remains in the mid-to-late stage of industrialization, where manufacturing remains the core growth engine, while the service sector is accelerating—a pattern consistent with China's status as a developing economy.

Table 2 Descriptive statistics

Variable	N	Max	Min	Mean	S.D	Median
isu	4050	0.805	0.038	0.398	0.089	0.392
gc	4050	0.099	0.006	0.046	0.017	0.046
gn	4050	1.593	0.043	0.173	0.087	0.155
fd	4050	7.451	0.112	0.908	0.577	0.743
ou	4050	28.368	0.001	0.189	0.539	0.085
gpa	4050	9.615	0.000	4.249	1.710	4.290
ul	4050	0.976	0.114	0.517	0.156	0.506

Correlation analysis

Table 3 Spearman correlation analysis coefficient table

	isu	*gc*	*ul*	*fd*	*gn*	*gpa*	*ou*
isu	1***						
gc	0.287***	1***					
ul	0.465***	0.257***	1***				
fd	0.645***	0.217***	0.508***	1***			
gn	0.219***	0.035**	-0.092***	0.263***	1***		
gpa	0.543***	0.358***	0.584***	0.558***	-0.051***	1***	
ou	0.175***	0.239***	0.359***	0.24***	-0.379***	0.312***	1***

Note: ***, **, *respectively represent 1%, 5% and 10% significance levels

The Spearman correlation analysis results are presented in Table 3. Most control variables show coefficients below 0.5, indicating no severe multicollinearity. Green credit is positively correlated with industrial structure upgrading, preliminarily suggesting that green credit may promote industrial upgrading. Notably, the strongest correlation is between industrial structure upgrading and financial development, suggesting substantial support for industrial transformation. Upgrading also correlates significantly with green patent applications, indicating technology's role in optimization.

2.3. Model

To simultaneously address confounding factors across individual and temporal dimensions while mitigating endogeneity, this study employs a time-individual fixed effects panel model to capture the interrelationships among variables. The proposed econometric specification is formulated as follows:

$$isu_{it} = \alpha + \beta_1 gc_{it} + \beta_2 gn_{it} + \beta_3 gpa_{it} + \beta_4 ul_{it} + \beta_5 fd_{it} + \beta_6 ou_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{2}$$

Where isu_{it} represents the explained variable, the level of industrial structure upgrading; gc_{it} represents the core explanatory variable, green credit; gpa_{it} represents the number of green patent applications; ul_{it} represents the urbanization level; fd_{it} represents the degree of financial development; ou_{it} represents the degree of opening up; α is the constant term; μ_i is the individual fixed - effect; λ_t is the time - fixed effect; and ε_{it} is the random error term.

3. Result and discussion

3.1. Benchmark results

Table 4 Benchmark regression results

	(1) *isu*	(2) *isu*	(3) *isu*	(4) *isu*	(5) *isu*	(6) *isu*
gc	2.387***	1.835***	0.608***	0.376***	0.366***	0.348***
	(30.250)	(23.082)	(8.367)	(5.999)	(5.828)	(5.559)
gn		0.337***	0.121***	0.134***	0.138***	0.146***
		(20.632)	(4.176)	(11.026)	(11.266)	(11.897)
gpa			0.028***	0.015***	0.015***	0.013***
			(29.048)	(20.847)	(20.767)	(17.035)
fd				0.072***	0.072***	0.068***
				(35.386)	(35.027)	(31.774)
ou					0.005**	0.003
					(2.472)	(1.597)
ul						0.049***
						(5.897)
constant	0.288***	0.255***	0.230***	0.229***	0.228***	0.214***
	(76.126)	(65.034)	(45.270)	(58.349)	(58.207)	(46.202)
Year	Yes	Yes	Yes	Yes	Yes	Yes
City	Yes	Yes	Yes	Yes	Yes	Yes
N	4050	4050	4050	4050	4050	4050
With-R^2	0.499	0.503	0.521	0.522	0.525	0.526

Note: ***, **, *respectively represent the significance levels of 1%, 5% and 10%, and t-statistics are reported in parentheses (The remaining table notes are the same).

Table 4 presents the panel fixed-effects regression results. Across all specifications (1) to (6), the coefficient for *gc* is positive and statistically significant at the 1% level, confirming its positive impact on industrial structure upgrading. This suggests green credit channels capital towards environmentally friendly industries, facilitating a shift towards higher value-added sectors, consistent with [18], who argue that green credit strengthens credit support for environmentally friendly and energy-saving industries, thereby providing sufficient financial resources to optimize industrial structure.

3.2. Heterogeneity effect

The baseline regression establishes green credit's positive influence on industrial upgrading. To uncover potential heterogeneity, this section examines differential effects among prefecture-level cities categorized according to their geographical location and economic development level.

Table 5 Heterogeneity effect results

ius	Economic development level		Geographical location	
	(1)	(2)	(3)	(4)
	Developed group	Underdeveloped group	Eastern group	Central and Western group
gc	0.079***	0.054***	0.062***	0.029*
	(5.384)	(4.438)	(3.541)	(1.851)
gn	0.014	0.197***	0.291***	0.157***
	(0.349)	(13.089)	(12.982)	(10.171)
gpa	0.343***	0.266***	0.262***	0.236***
	(12.102)	(17.928)	(12.444)	(12.705)
fd	0.386***	0.460***	0.361***	0.434***
	(5.666)	(23.475)	(14.671)	(23.547)
ou	0.002	-0.058**	0.017	-0.039**
	(0.221)	(-2.020)	(0.397)	(-2.537)
ul	0.122***	0.106***	0.124***	0.073***
	(4.662)	(7.403)	(6.004)	(3.912)
constant	0.001	0.037***	0.005	0.001
	(0.018)	(3.276)	(0.735)	(0.017)
Year	Yes	Yes	Yes	Yes
City	Yes	Yes	Yes	Yes
N	612	3438	1512	2538
With-R^2	0.525	0.491	0.705	0.468

(1) Heterogeneity effect of economic development level

To further reveal the regional heterogeneity of green credit’s impact on industrial structure upgrading, this study aligns with [19] to classify cities based on economic development levels. Specifically, we use the median annual GDP per capita as the threshold: cities above the median are categorized into the "developed group," while those below form the "underdeveloped group." Subgroup regression analyses are then conducted.

As shown in Table 5 columns (1)-(2), green credit significantly promotes industrial upgrading in all regions. However, its effect is stronger in developed regions. This disparity may stem from their more mature financial markets and efficient capital allocation, which better direct green credit towards high-value-added industries, aligning with provincial evidence from [20]. Economic development level therefore influences green credit's impact.

(2) Heterogeneity effect of geographical location

Following the regional classification of the National Bureau of Statistics (NBS) outlined in its January 2017 report on 2016 real estate development, this study groups prefecture-level cities into an eastern group and a central-western group to analyze geographical heterogeneity[21]. The eastern region adheres to the NBS classification, comprising Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan. On the contrary, the remaining provinces are classified as the central and western regions.

Table 5 columns (3)-(4) reveal a significantly stronger green credit effect on industrial upgrading in eastern regions compared to non-eastern. This regional advantage likely stems from the east's superior economic base, financial infrastructure, and high-tech industry concentration, which enhance the efficiency of converting green capital into technological innovation and clean production. This aligns with [18], which emphasize eastern coastal regions' natural advantages and rapid regional economic growth. Additionally, synergistic integration of producer services with traditional industries further accelerates green transformation in the east. Geography thus moderates green credit's impact.

3.3. Robustness tests

Table 6 Robustness test results

	(1) *isu*(POOL)	(2) *isu*(RE)	(3) isu_a	(4) isu_b
gc	0.406***	0.405***	0.059***	0.035***
	(5.607)	(5.384)	(4.218)	(3.229)
gn	-0.023	0.015	0.057***	-0.037**
	(-1.478)	(0.349)	(2.885)	(-2.099)
gpa	0.019***	0.018***	0.166***	0.350***
	(18.801)	(12.102)	(8.584)	(19.259)
fd	0.059***	0.060***	0.474***	0.273***
	(21.978)	(5.666)	(23.487)	(11.979)
ou	0.001	0.000	-0.035	0.086***
	(0.345)	(0.221)	(-0.960)	(3.097)
ul	0.075***	0.070***	0.013	0.207***
	(5.622)	(4.662)	(0.565)	(9.381)
constant	0.209***	0.211***	-0.026***	0.019
	(44.645)	(33.356)	(-3.082)	(0.564)
Year	No	No	Yes	Yes
City	No	No	Yes	Yes
N	4050	4050	4050	4050
With-R^2	0.503	0.525	0.362	0.548

To ensure the robustness of the baseline findings, this study employs alternative model specifications and variable measurements. The results of these robustness tests appear in Table 6.

(1) Alternative model

Columns (1)-(2) of Table 6 report the results of pooled OLS (POOL) and random effects (RE) models. The green credit coefficient remains statistically significant at the 1% level with positive values across both specifications, consistent with Table 2. The findings confirm that green credit's positive impact on industrial structure upgrading persists under different model specifications, thereby enhancing the reliability of baseline regression results.

(2) Alternative dependent variable

Following [22], this study constructs an industrial structure hierarchy coefficient (isu_a) by applying differential weights (1, 2, 3) to the added values of three industrial tiers. Additionally, we adopt the ratio of tertiary industry value-added to secondary industry value-added (isu_b)as an alternative indicator, per [18]. Columns (3)-(4) of Table 6 present regression results using isu_a and isu_b. The green credit coefficient remains statistically significant at the 1% level with positive values, aligning with Table 2. These results demonstrate that despite methodological differences in measuring industrial structure upgrading, green credit's promotional effect on structural transformation remains robust. At the prefecture-level, green credit consistently drives industrial upgrading.

4. Conclusion

4.1. Conclusions

This research conducts an empirical analysis of how green credit influences industrial structure upgrading, utilizing panel data from 225 prefecture-level cities in China covering the period 2005–2022. Empirical results show that green credit significantly promotes industrial structure upgrading, with this effect being more evident in developed regions and eastern provinces. Robustness tests through alternative model specifications and dependent variable measurements confirm the universal and sustainable nature of green credit's positive promotion effect on industrial transformation.

There are a few limitations to note. First, city-level data may miss firm-level factors. Second, using GDP share to measure industrial upgrading may overlook technology and environmental efficiency. Third, the static approach doesn't account for long-term changes. Future research should: (1) use firm-level data; (2) develop better measures of industrial upgrading; and (3) use dynamic models.

4.2. Policy implications

Informed by the empirical results, this research formulates concrete policy suggestions aimed at enhancing green credit's role in facilitating industrial structure advancement.

(1) Governments should coordinate better to make green credit more efficient—by using interest subsidies, guarantees and risk-funds to boost bank lending—since green credit helps upgrade industry.

(2) Governments should set up green credit partnerships across regions—linking eastern financial institutions with central and western projects through joint loans and approvals—to balance development and boost green-driven industrial change nationwide.

(3) Commercial banks should adopt tailored green credit policies, focusing on high-value, low-energy industries in developed areas to drive innovation, and supporting renewable energy projects in central and western regions to leverage industrial transfer opportunities. This approach is backed by the study's findings.

Reference

[1] Li R, Luo Y. Green credit and regional industrial structure upgrading: evidence from China [J]. Finance Res. Lett., 2024, 65: 105472.

[2] Lu H, Pan Y, Fan R, Guan W. Green credit policy and heavily polluting enterprises' green transition [J]. Int. Rev. Financ. Anal., 2025, 103: 104162.

[3] Kamali Saraji M, Streimikiene D. Challenges to the low carbon energy transition: a systematic literature review and research agenda [J]. Energy Strategy Rev., 2023, 49: 101163.

[4] Tan W, Huang Y, Chen X H, Gatto A. Green credit policy and energy consumption intensity in China: firm-level evidence and insights [J]. J. Environ. Manage., 2025, 373: 123664.

[5] Wan J, Niu Z, Li B. Does fintech improve the carbon reduction effect of green credit policy? Evidence from China [J]. Econ. Anal. Policy, 2025, 85: 1258–1269.

[6] Jia H, Li R, Guo Y, Zhao Z. Research on corporate environmental investment behaviour driven by green credit policies [J]. Int. Rev. Financ. Anal., 2025, 97: 103800.

[7] Zhou C, Sun Z, Qi S, Li Y, Gao H. Green credit guideline and enterprise export green-sophistication [J]. J. Environ. Manage., 2023, 336: 117648.

[8] Dou W, Zhang H, Miao B, Wang B. How do analyst attention and green credit promote corporate green innovation? [J]. Int. Rev. Econ. Finance, 2025, 99: 104037.

[9] Ge S, Luo X, Li Y, Zheng L. The impact of green credit policy on total factor productivity of enterprises [J]. Int. Rev. Econ. Finance, 2024, 95: 103480.

[10] Wang J, Huang H, Nawaz Khan A, Liao Y, Zang D. Inhibit or stimulate? Green credit guidelines and corporate financialization [J]. J. Cleaner Prod., 2024, 470: 143303.

[11] Zheng W, Zhang L, Hu J. Green credit, carbon emission and high quality development of green economy in China [J]. Energy Rep., 2022, 8: 12215–12226

[12] Wang M X, Huang L, Chen Z M. The impact of green financial policy on the regional economic development level and AQI—evidence from Zhejiang province, China [J].

[13] Zhang G, Zhang P, Zhang Z G, Li J. Impact of environmental regulations on industrial structure upgrading: an empirical study on Beijing-Tianjin-Hebei region in China [J]. J. Cleaner Prod., 2019, 238: 117848.

[14] Kuznets S, Murphy J T. Modern economic growth: rate, structure, and spread [M]. New Haven: Yale University Press, 1966.

[15] He L, Zhang L, Zhong Z, Wang D, Wang F. Green credit, renewable energy investment and green economy development: empirical analysis based on 150 listed companies of China [J]. J. Cleaner Prod., 2019, 208: 363–372.

[16] Hu Y, Zheng J. How does green credit affect carbon emissions in China? A theoretical analysis framework and empirical study [J]. Environ. Sci. Pollut. Res., 2022, 29(39): 59712–59726.

[17] Qiu Y, Wang H, Wu J. Impact of industrial structure upgrading on green innovation: evidence from Chinese cities [J]. Environ. Sci. Pollut. Res., 2023, 30(2): 3887–3900.

[18] Hu Y, Jiang H, Zhong Z. Impact of green credit on industrial structure in China: theoretical mechanism and empirical analysis [J]. Environ. Sci. Pollut. Res., 2020, 27(10): 10506–10519.

[19] Ran C, Zhang Y. The driving force of carbon emissions reduction in China: does green finance work? [J]. J. Cleaner Prod., 2023, 421: 138502.

[20] Dang C L. The relationship between regional green finance development and industrial structure: an empirical analysis based on China's provincial panel [J]. Bus. Econ. Res., 2019, 15: 143–145.

[21] Li Y, Hu H, Li H. Empirical analysis of the impact of green credit on the upgrading of China's industrial structure: based on Chinese provincial panel data [J]. On Econ. Probl., 2020, 1: 37–43.

[22] Nian W, Dong X. Spatial correlation study on the impact of green financial development on industrial structure upgrading [J]. Front. Environ. Sci., 2022, 10: 1017159.