Economic Society and Humanities Vol. 3 No. 2, 2026

Academic Education Publishing House

Research on the Impact of Green Credit on Carbon Emissions of Heavily Polluting Enterprises

Jiacheng Ding
Jiangxi Normal University, Nanchang, Jiangxi, China

Abstract: Heavily polluting enterprises are a significant component of China's industrial system, and their low-carbon transition is a critical step in achieving the dual carbon goals. An in-depth study of the impact of green credit on the carbon emissions of heavily polluting enterprises contributes to the implementation of the dual carbon targets. This paper selects panel data from Shanghai and Shenzhen A-share listed companies from 2007 to 2022, using the 2012 "Green Credit Guidelines" as a quasi-natural experiment, and constructs a difference-in-differences model to investigate the impact and mechanisms of green credit on the carbon emissions of heavily polluting enterprises. The results show that: (1) Green credit policies significantly suppress the carbon emissions of heavily polluting enterprises, and this conclusion remains valid after a series of robustness tests; (2) Green credit policies can curb the carbon emissions of heavily polluting enterprises through external financing constraints and Corporate Green Technology Innovation; (3) Corporate reputation plays a positive moderating role in the process of green credit policies restraining carbon emissions of heavily polluting enterprises; (4) The effectiveness of green credit policies in reducing corporate carbon emissions varies significantly across regions and levels of corporate transparency.

Keywords: Green Credit Policy; Corporate Carbon Emissions; Financing Constraints; Corporate Green Technology Innovation

1. Introduction

China's economy has transitioned from a phase of high-speed growth to one of high-quality development, where carbon reduction has emerged as an essential pathway. During the general debate of the 75th United Nations General Assembly in September 2020,China would scale up its Nationally Determined Contributions (NDCs) and implement more robust policies to ensure that CO2 emissions peak before 2030 and carbon neutrality is achieved by 2060.As a primary source of national emissions, heavily polluting industries—characterized by high energy consumption, high emissions, and high pollution (the "three-high" problem)—are critical areas for carbon mitigation research. Therefore, investigating the impact of green credit on carbon emissions within these sectors is of profound significance.

The Green Credit Guidelines, issued by the former China Banking Regulatory Commission in February 2012, marked the formal establishment of China's green credit framework. These guidelines encourage financial institutions to redirect resources toward green industries, effectively internalizing the negative externalities associated with corporate pollution. This policy framework provides a foundational basis for analyzing how green credit facilitates carbon reduction in heavily polluting firms. In 2018, the People's Bank of China (PBOC) issued the Notice on the Performance Evaluation of Green Credit for Banking Deposit-Taking Financial Institutions, further integrating evaluation results into the Macro-Prudential Assessment (MPA) to implement incentive and disciplinary measures. Guided by these policies, banks have actively expanded their green credit businesses. By the end of 2023, China's green credit balance exceeded 30 trillion RMB, with loans directed toward projects with direct and indirect carbon reduction benefits totaling 10.43 trillion and 9.81 trillion RMB, respectively—collectively accounting for 67.3% of the total balance. As the primary entities responsible for environmental pollution, heavily polluting enterprises play a decisive role in China's pursuit of sustainable development and cleaner production.

2. Literature Review

Corporate carbon emission performance is frequently measured through carbon reduction technologies, also known as low-carbon technologies, which aim to minimize carbon intensity. Scholars have extensively debated the determinants of corporate emissions, categorizing them into three primary dimensions. First, the technological innovation perspective highlights how digital transformation reduces knowledge management costs and enhances resource allocation efficiency, thereby amplifying green innovation capabilities [1,2]. Furthermore, digital tools such as big data and AI resolve information silos, optimizing environmental management systems and further catalyzing emission reductions [3]. Second, the industrial agglomeration perspective offers evolving conclusions. While earlier literature associated agglomeration with increased pollution [4], recent studies emphasize "green spillovers." Inter-firm symbiotic networks facilitate the flow of environmental resources and collaborative innovation, achieving significant reductions particularly in state-owned and heavily polluting sectors [5]. However, evidence increasingly points toward a complex, non-linear relationship between agglomeration and carbon performance, contingent upon the developmental stage and institutional environment. Third, the policy-driven perspective reveals divergent results based on policy instruments. Market-based tools, such as carbon trading, force low-carbon transitions by internalizing costs, whereas command-and-control regulations often exhibit threshold effects: firms may initially adopt "resistant" responses until regulatory costs surpass a critical point, after which they pivot toward substantive green innovation [6] .Carbon Emissions As green credit policies evolve, sustainable finance has become a central research theme at both macro and micro levels. At the macro level, green credit serves as a pivotal financial instrument for correcting "carbon externalities." It redirects capital toward green industries through preferential pricing while raising financing barriers for heavily polluting sectors, thereby reducing the carbon elasticity of economic growth [7]. Furthermore, differentiated credit pricing encourages structural shifts toward high-value-added, low-energy sectors. However, these effects are often non-linear and exhibit regional heterogeneity, appearing more pronounced in eastern regions with higher marketization. At the micro level, green-labeled loans significantly alleviate funding bottlenecks for eco-friendly firms, enabling increased R&D investment in clean equipment [8]. Conversely, heavily polluting firms face a "punishment-then-incentive" dynamic: initial credit constraints may "crowd out" green innovation due to liquidity pressure, but once interest rate spreads exceed a critical threshold, the high cost of non-compliance compels firms to invest in green technologies to regain credit access [9].

Marginal Contributions this study contributes to the literature in three aspects: First, by focusing on corporate-level emissions, it extends the environmental impact of green credit to micro-entities, broadening the existing research scope. Second, it identifies two distinct transmission pathways—environmental concern and financing constraints—while incorporating corporate reputation as a moderating factor, thereby addressing core questions regarding the evolution of China’s green financial system. Third, by examining heterogeneity across regional characteristics and corporate transparency, this paper evaluates the contextual effectiveness of green credit, providing empirical evidence for the precise implementation of policies and the unleashing of corporate emission reduction potential.

3. Theoretical Analysis and Research Hypotheses

3.1 Green Credit and Carbon Emissions of Heavily Polluting Enterprises Green Credit Embodies the Dual Attributes of "Environmental Screening" and "Financial Incentives"

Embedding environmental externalities into the capital allocation process. On one hand, banks provide differential financing based on green credit policies, offering interest rate discounts and credit priority to environmentally friendly firms to alleviate their liquidity constraints. Conversely, for heavily polluting enterprises, these policies raise financing barriers through higher interest rates and credit limits. This compels firms to integrate green principles into their ongoing operations, thereby reducing carbon emissions. On the other hand, unlike traditional command-and-control environmental regulations, green credit replaces compulsory penalties with market-based signals, which typically encounter less corporate resistance and offer stronger incentives. To secure credit support, heavily polluting firms are incentivized to enhance low-carbon innovation, adopt pollution abatement practices, and improve energy conversion efficiency. From a long-term perspective, these firms increase environmental investment to achieve low-carbon upgrades. Accordingly, we propose:

Hypothesis 1 (H1): Green credit policies significantly reduce the carbon emission intensity of heavily polluting enterprises.

3.2 The Transmission Mechanisms of Green Credit on Carbon Emissions

Financing Constraint Effect Financing constraints reflect the limitations firms face in accessing and utilizing capital—a pervasive challenge during corporate transitions, particularly for heavily polluting firms under increasing sustainability pressures. Green credit policies redirect social capital toward green sectors, effectively functioning as a "bridge" between policy implementation and emission reduction. By intensifying financing constraints on heavily polluting firms, a "forced-out" mechanism is established, obliging firms to curtail high-carbon production and shift toward clean energy. This redirection of limited capital toward green domains often compresses productive investment, leading to reduced industrial output and lower carbon emissions. Specifically, large-scale polluters adopt more aggressive mitigation measures to maintain access to essential credit resources.

Hypothesis 2 (H2): Green credit policies reduce carbon emissions by imposing credit-channel constraints on the investment and financing activities of heavily polluting enterprises.

3.3 The Moderating Effect of Corporate Reputation Corporate reputation

Built through long-term public image and stakeholder evaluation, reflects a firm's social trust and market influence. In the context of green credit, reputation serves as a critical variable moderating the emissions of "double-high" (high-energy, high-pollution) firms through both positive incentives and negative warnings. A superior reputation strengthens a firm's motivation to increase environmental R&D, as proactive low-carbon practices earn social acclaim and improve market competitiveness. This attracts investors and broadens financing channels, creating a virtuous cycle of resource allocation. Conversely, for firms burdened with negative reputations due to pollution, green credit policies further tighten financing constraints, forcing them to pursue green transitions to restore their public image and avoid potential public boycotts or regulatory penalties.

Hypothesis 3 (H3): Corporate reputation plays a positive moderating role in the relationship between green credit and carbon emission reduction in heavily polluting enterprises.

4. Research Design

4.1 Model Construction

To investigate the impact of green credit policies on the carbon emissions of heavily polluting enterprises, this study constructs a multi-period Difference-in-Differences (DID) model as follows:

$$CO_{2i,t}=\alpha_0+\alpha_1 post_{i,t} * treat_{i,t}+\alpha_2 controls_{i,t}+\gamma_t \quad (1)$$

Where $CO_{2i,t}$ is the dependent variable, representing the natural logarithm of carbon emission intensity for firm i in year t. $treat_{i,t}$ is a group dummy variable, assigned a value of 1 if the firm belongs to a heavily polluting industry and 0 otherwise. $post_{i,t}$ is a policy time dummy variable, assigned a value of 1 for the year 2012 and thereafter (following the issuance of the Guidelines), and 0 for the years prior. $controls_{i,t}$ represents a set of control variables. γ_t and μ_i denote individual and time fixed effects, respectively, while $\varepsilon_{i,t}$ is the random error term.

4.2 Variable Definitions and Data Sources

4.2.1 Variable definitions

(1) Dependent variable: Due to the scarcity of voluntary carbon disclosure, we calculate this by integrating firm-level operating costs with sector-specific energy consumption data and CO2 conversion coefficients.

(2) Core explanatory variable: The interaction term $post_{i,t} * treat_{i,t}$ serves as the primary regressor. We utilize the 2012 Green Credit Guidelines as a quasi-natural experiment, setting 2012 as the policy implementation year. Firms are categorized into the treatment group if their industry codes align with the list of 15 "double-high" (high-pollution, high-energy) industries.

(3) Control variables: To isolate the policy effect, we control for several firm-level factors: Firm Age (Age), measured by the log of years

since listing; Firm Size (Size), proxied by the log of total assets; Leverage (Lev), the debt-to-asset ratio; Return on Assets (ROA), reflecting financial health; Cash Flow (Cashflow), indicating liquidity for green investment; Duality (Dual), a dummy for CEO-Chair separation; and Tobin's Q (TobinQ), representing market valuation and innovation potential.

4.2.2 Data sources

The initial sample comprises China's A-share listed companies from 2007 to 2023. Following standard conventions, we excluded: (1) financial and insurance firms; (2) firms with abnormal leverage ratios (less than 0 or greater than 1); (3) ST, *ST, and PT firms; and (4) observations with missing data. The final balanced panel consists of 21,492 observations. Data were sourced from the China Energy Statistical Yearbook, China Industrial Economy Statistical Yearbook, CSMAR, EPS, and the Marketization Index databases.

4.3 Empirical Results of Green Credit's Impact on Carbon Emissions

4.3.1 Descriptive statistics

Table 1 presents the descriptive statistics for both the treatment and control groups. The results indicate that the mean value of the natural logarithm of corporate carbon emissions lnCO2 is 1.67, with a range spanning from a minimum of -12.85 to a maximum of 12.32. These figures suggest that while the overall distribution of carbon emissions across the sampled firms is relatively balanced, there exists substantial cross-sectional variation in emission levels among individual enterprises.

For Example:

Table 1. Variable Descriptions and Descriptive Statistics

Variable	Sample size	Mean	Standard deviation	Minimum	Maximum
lnCO2	21942	1.670	2.102	-12.85	12.32
did	21942	0.266	0.442	0.000	1.000
age	21942	7.205	6.756	-6	30
size	21942	21.91	1.311	16.64	28.64
lev	21942	0.385	0.185	0.00752	1.380
roa	21942	0.0568	0.0690	-1.235	1.285
cashflow	21942	0.0578	0.0763	-1.788	4.218
dual	21942	0.301	0.459	0	1
soe	21942	0.332	0.471	0	1
tobinq 1	21942	1.945	1.251	0.681	22.57

4.3.2 Baseline regression analysis

To quantify the impact of green credit on corporate carbon reduction, we employ the Difference-in-Differences (DID) method, with results presented in Table 2. Column (1) displays the regression results of the core explanatory variable on corporate carbon emissions, while Column (2) incorporates the full set of control variables. The results indicate that, regardless of the inclusion of control variables, the coefficients of the green credit policy remain negative and statistically significant at the 1% level. This consistently negative and significant relationship provides strong empirical evidence for Hypothesis 1, confirming that green credit policies effectively reduce carbon emission levels among heavily polluting enterprises.

Table 2. Benchmark Regression Results

	(1)	(2)
	lnCO2	lnCO2
did	-0.433***	-0.425***
	(0.010)	(0.010)
_cons	9.242***	9.472***
	(0.017)	(0.111)
N	21942	21942
R2	0.570	0.534
id	YES	YES
year	YES	YES
F	1310.672	845.621

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively, and robust standard errors are reported in parentheses.

4.3.3 Robustness checks

(1) Parallel trend test

The parallel trend test is a fundamental prerequisite for employing the Difference-in-Differences (DID) method to evaluate the efficacy of green credit policies. Its core objective is to ensure that the treatment and control groups exhibit homogenous carbon emission trends prior to the policy intervention. Using the event study approach, we examine the annual effects of the green credit policy. The

Academic Education Publishing House

parallel trend assumption holds if the regression coefficients for the years preceding the policy implementation are statistically insignificant. As shown in Figure 1, Since the Green Credit Guidelines were implemented in 2012, we designate 2012 as the base year, with pre_1, pre_2, and pre_3representing one, two, and three years prior to the policy, and post_1, post_2,and post_3 representing the subsequent years.

The empirical results indicate that during the pre-intervention period, the coefficients for all years fail to pass the significance test. This suggests no fundamental difference in emission behavior between heavily polluting and non-heavily polluting enterprises at the initial stage, thereby satisfying the parallel trend assumption. Although the treatment group showed a slight downward inclination just before the policy node, this is primarily attributable to anticipatory responses: heavily polluting firms, foreseeing stricter future regulations and potential credit constraints, preemptively adjusted their investment scales and production modes. Following the formal execution of the policy, the regression coefficients for subsequent years turned significantly negative, clearly revealing the substantial contribution of green credit instruments in driving the low-carbon transition of heavily polluting industries.

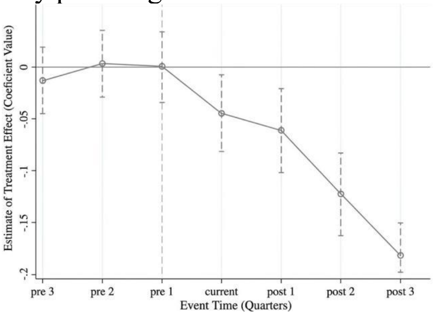

Figure 1. Test for Parallel Trends

(2) Placebo test

To rule out the possibility that our primary results are driven by unobserved random factors, we conduct a placebo test by randomly assigning the treatment status to firms in the sample. As shown in Figure 2, the estimated coefficients derived from 500 (or 1,000) random iterations are centered around zero and closely follow a normal distribution. This pattern indicates that the observed impact of green credit on corporate carbon emissions is not a product of stochastic elements or omitted variables. Consequently, the placebo test further validates the robustness and causal reliability of our baseline regression results.

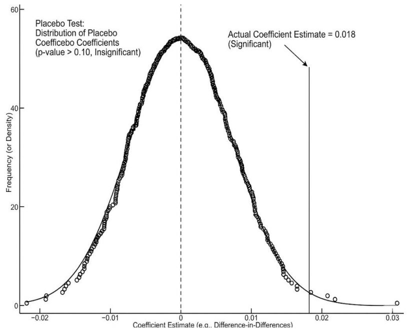

Figure 2. Placebo Test

(3) PSM-DID

Test The implementation of the Green Credit Guidelines serves as a quasi-natural experiment to assess policy impacts on enterprises. However, since the policy is an exogenous shock, utilizing the Difference-in-Differences (DID) method alone may encounter endogeneity issues stemming from selection bias. To address this, we conduct a Propensity Score Matching (PSM) test to ensure that each firm in the treatment group is matched with a comparable counterpart in the control group. By mitigating selection bias and bringing the quasi-natural experimental environment closer to a randomized controlled trial, the PSM-DID approach enhances the robustness and credibility of our findings. We employ the nearest-neighbor matching method and re-estimate Equation (1) using the matched sample. As shown in Column (2) of Table 3, the coefficient of the core explanatory variable is -0.433, which is significant at the 1% level and remains highly consistent with the baseline regression results. This indicates that after accounting for potential sample self-selection bias, the inhibitory effect of green credit on the carbon emissions of heavily polluting enterprises remains significant, thereby reinforcing the fundamental conclusions of this study.

Table 3. Benchmark Regression Results Based on PSM-DID

	(1)	(2)
	lnCO2	Psm-did
did	-0.425***	-0.433***
	(0.010)	(0.047)
_cons	9.472***	9.7842***
	(0.111)	(0.434)
N	21942	9,507
R2	0.534	0.526
id	YES	YES
year	YES	YES

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively, and robust standard errors are reported in parentheses.

5. Mechanism Analysis

5.1 External Financing Constraint Effect

Based on the previous theoretical analysis, to verify Hypothesis 2, this study constructs a three-stage mediation model to examine the transmission mechanisms through which green credit policies affect the carbon emissions of heavily polluting enterprises:

$$SA_{i,t} = \beta_0 + \beta_1 time_{i,t} * treat_{i,t} + \beta_2 control_{i,t} + \varphi_t + \mu_i + \varepsilon_{i,t} \quad (2)$$

$$CO_{2i,t} = \gamma_0 + \gamma_1 post_{i,t} * treat_{i,t} + \gamma_2 SA_{i,t}, + \gamma_3 control_{i,t} + \varphi_t + \mu_i + \varepsilon_{i,t} \quad (3)$$

Where $SA_{i,t}$ represents the mediating variables, specifically financing constraints and corporate environmental concern. We utilize the SA index to measure financing constraints, as it avoids potential endogeneity issues inherent in the KZ and WW indices [10]. The SA index is calculated as:-0.737* Size + 0.043* Size ² — 0.04* Age. In Table 4, Column (1) reports the baseline total effect, confirming that green credit policies significantly inhibit carbon emissions in heavily polluting firms relative to the control group. Column (2) examines the impact of the policy on financing constraints; the regression coefficient for the core explanatory variable is 0.133 and statistically significant, indicating that the policy implementation has intensified financing hurdles for these firms. Column (3) simultaneously incorporates the policy dummy and financing constraints into the regression. While the core explanatory variable remains significant, the mediator's coefficient is not statistically significant in this specific specification. We conducted a Sobel test for further verification. The resulting Z-value of 13.38 significantly exceeds the critical threshold, with the mediating effect accounting for 25.6% of the total effect. This provides robust evidence that financing constraints serve as a partial mediator in the relationship between green credit and carbon reduction, thereby supporting Hypothesis 2.

Table 4. The Intermediary Effect of Financing Constraints

	(1)	(2)	(3)
	lnCO2	SA	lnCO2
did	-0.659***	0.133***	-0.631***
	(0.009)	(0.003)	(0.009)
SA			-0.153***
			(0.020)
_cons	10.523***	0.119***	7.775***
	(0.087)	(0.032)	(0.089)
id	YES	YES	YES
year	YES	YES	YES
N	21942	20676	20676
R^2	0.311	0.904	0.417
adj. R^2	0.228	0.894	0.355
Sobel Z		13.38***	

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively, and robust standard errors are reported in parentheses.

5.2 The Moderating Effect of Corporate Reputation

Based on the preceding theoretical analysis, to verify Hypothesis 3, this study constructs a moderating effect model to examine how corporate reputation influences the relationship between green credit and carbon emissions:

$$CO_{2i,t} = \theta_0 + \theta_1 post_{i,t} * treat_{i,t} + \theta_3 comrep_{i,t} + \theta_4 (post_{i,t} * treat_{i,t}) * comrep_{i,t} + \theta_5 control_{i,t} + \varphi_t + \mu_i + \varepsilon_{i,t} \quad (4)$$

Where $comrep_{i,t}$ represents the moderating variable, corporate reputation. To mitigate potential multi-collinearity issues, the core explanatory variable $time_{i,t} * treat_{i,t}$ and the moderator $comrep_{i,t}$ are mean-centered before constructing the interaction term $(time_{i,t} * treat_{i,t}) * comrep_{i,t}$.

We employ factor analysis to construct a comprehensive evaluation index for corporate reputation, integrating four dimensions: consumer and social perspective, creditor perspective, shareholder perspective, and the firm’s internal perspective. As reported in Columns (1) and (2) of Table 5, the coefficient of the interaction term between corporate reputation and the core explanatory variable is -0.009, which is statistically significant at the 1% level. This result indicates that corporate reputation exerts a positive moderating effect on the relationship between green credit policies and carbon reduction. Specifically, a superior reputation amplifies the inhibitory impact of green credit on corporate carbon emissions, thereby supporting Hypothesis 3.

Table 5. Modulating Effect

Variable	(1)	(2)
	lnCO2	lnCO2
did	-0.527***	-0.317***
	(0.011)	(0.002)
comrep		0.210***

		(0.028)
comrep*(time*treat)		-0.009 ***
		(0.003)
id	YES	YES
year	YES	YES
N	15397	15397
R^2	0.713	0.713
adj. R^2	0.712	0.712

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively, and robust standard errors are reported in parentheses.

5.3 Regional Heterogeneity

To further explore the heterogeneous impact of green credit policies on the carbon emissions of heavily polluting enterprises and to provide robust evidence for the established mechanisms, this section conducts a sub-sample analysis across four geographical regions. Regional disparities often influence corporate production, environmental activities, and financing capabilities. Following conventional research, we divide the sample into Eastern, Central, Western, and Northeastern regions and perform separate regressions.

Columns (1) to (3) in Table 6 report the regression results for the Eastern, Central, Western, and Northeastern regions, respectively. The results indicate that the coefficients for $Treat \times Post$ are significantly negative across all four regions. Notably, the carbon reduction effect is most pronounced in the Northeast and least significant in the Central region. This suggest that green credit policies exert the strongest inhibitory effect on heavily polluting enterprises located in Northeast China. A plausible explanation is that the Northeast has long been characterized by a high concentration of heavy industries, which predominantly fall into the heavily polluting category. Compared to the Eastern region, which has already achieved a higher degree of industrial cleaning, the Northeast possesses lower marginal abatement costs, leading to a larger reduction in carbon emissions. Conversely, the Central region primarily undertook the transfer of labor-intensive industries (such as electronics and textiles) from the East between 2006 and 2015. Since these sectors possess inherently lower carbon intensities, the emission reduction "headroom" provided by green credit is naturally smaller than that of the heavy industrial clusters (steel, coal, and chemicals) in the Northeast.

Table 6. Regional Heterogeneity

	(1)	(2)	(3)	(4)
Variable	Eastern	Central	West	Northeast
did	0.519***	0.354***	0.645***	0.753***
	(0.0145)	(0.0269)	(0.0358)	(0.0679)
Controls	YES	YES	YES	YES
id	YES	YES	YES	YES
year	YES	YES	YES	YES
N	12679	2635	2205	645
R^2	0.328	0.290	0.312	0.333
adj. R^2	0.244	0.203	0.226	0.233

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively, and robust standard errors are reported in parentheses.

5.4 Heterogeneity in Corporate

Transparency The impact of green credit policies on carbon reduction may vary depending on the degree of corporate transparency. To explore this, we categorize the sample into four tiers based on transparency ratings: Excellent, Good, Qualified, and Unqualified. The estimation results are presented in Table 7. The findings reveal that for the "Unqualified" group, the regression coefficient of the core explanatory variable is near zero and statistically insignificant. Conversely, for firms with "Excellent," "Good," and "Qualified" transparency, the coefficients are significantly negative, with the strongest inhibitory effect observed in the "Excellent" group.

This suggests that green credit policies are most effective in reducing emissions for firms with high transparency. A plausible explanation is that highly transparent enterprises tend to prioritize environmental responsibility and sustainable development, which reduces information asymmetry and makes it easier for them to secure green financing. Consequently, the carbon reduction potential of green credit is more fully realized in these firms. In contrast, firms with poor transparency face greater difficulty in accessing green credit support, resulting in their carbon emissions being relatively unresponsive to such policy incentives.

Table 7. Heterogeneity in Corporate Transparency

	(1)	(2)	(3)
Variable	Excellent corporate transparency	Good corporate transparency	Pass corporate transparency

did	-0.369***	-0.350***	-0.340***
	(0.0255)	(0.0141)	(0.0592)
Controls	YES	YES	YES
id	YES	YES	YES
year	YES	YES	YES
N	2590	8218	1178
R^2	0.395	0.357	0.414
adj. R^2	0.065	0.176	-0.333

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively, and robust standard errors are reported in parentheses.

7. Policy Implications

To achieve sustainable development, it is imperative to implement measures that reduce carbon emissions and enhance carbon neutrality performance. This is not only an inevitable choice for ecological protection but also a critical pathway to elevating socio-economic development. Realizing corporate low-carbon transitions requires the strategic utilization of green credit to direct capital toward green innovation projects. Based on panel data of Chinese listed companies from 2007 to 2022, this study systematically investigates the impact and mechanisms of green credit policies on carbon reduction using a Difference-in-Differences (DID) approach. The results indicate that green credit significantly inhibits carbon emissions in heavily polluting firms, a finding that remains robust across various tests. Furthermore, the carbon reduction effect exhibits significant heterogeneity, appearing more pronounced among small-scale firms, firms in highly competitive industries, and those in financially developed regions. The primary transmission pathways include the improvement of environmental information disclosure quality and the contraction of debt financing scales.

This study provides micro-level evidence for the efficacy of green credit policies and highlights their role in facilitating corporate transitions. The policy implications are as follows: First, the green credit policy framework should be further refined to establish a long-term operational mechanism. Financial institutions must strictly adhere to policy requirements while avoiding "one-size-fits-all" execution. They should strengthen debt financing constraints for heavy polluters while providing targeted credit support for technological upgrades and pollution control. Second, policy implementation should account for institutional and industrial disparities. In regions with high environmental regulation, authorities should leverage diverse tools to mitigate emissions; in regions with lower regulation, market-based incentives and enforcement against major polluters must be strengthened. Additionally, credit resource allocation should be optimized across industries with varying capital intensities to incentivize environmental corporate social responsibility (CSR). Third, the environmental information disclosure mechanism must be improved. A unified national standard for corporate environmental disclosure should be established to ensure information accuracy and comparability. Incentives such as tax breaks or credit preferences should be granted to firms with high-quality disclosure, while penalties should be imposed for concealment or misreporting. Fourth, debt financing structures should be optimized to catalyze green transitions. Financial institutions are encouraged to innovate green products—such as carbon-linked loans and energy-efficiency improvement loans—to meet the diversified financing needs of transitioning enterprises.

References

[1] Blichfeldt H, Faullant R. Performance effects of digital technology adoption and product &service innovation–A process-industry perspective. Technovation, 2021, 105: 102275.
[2] Chen P. Relationship between the digital economy, resource allocation and corporate carbon emission intensity: New evidence from listed Chinese companies. Environmental Research Communications, 2022, 4(7): 075005.
[3] Wu D, Xie Y, Lyu S. Disentangling the complex impacts of urban digital transformation and environmental pollution: Evidence from smart city pilots in China. Sustainable Cities and Society, 2023, 88: 104266.
[4] Cheng Z. The spatial correlation and interaction between manufacturing agglomeration and environmental pollution. Ecological indicators, 2016, 61: 1024-1032.
[5] Shen N, Peng H. Can industrial agglomeration achieve the emission-reduction effect? Socio-Economic Planning Sciences, 2021, 75: 100867.
[6] He F, Duan L, Cao Y, et al. Green credit

policy and corporate climate risk exposure. Energy Economics, 2024, 133: 107509.
[7] He J, Xue H, Yang W, et al. Green credit policy and corporate green innovation. International Review of Economics & Finance, 2025, 99: 104031.
[8] Lu Q, Deng Y, Wang X, et al. The impact of China's green credit policy on enterprise digital innovation: evidence from heavily-polluting Chinese listed companies. China Finance Review International, 2024, 14(1): 103-121.
[9] Ma D, He Y, Zeng L. Can green finance improve the ESG performance? Evidence from green credit policy in China. Energy Economics, 2024, 137: 107772.
[10]Hadlock C, J Pierce. New Evidence on Measuring Financial Constraints: Moving Beyond the KZ Index. Review of Financial Studies, 2010, Vol. 23 (5), 1909—1940.