

Research on the Impact of China's Green Credit Policy on the ESG Level of Enterprises

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Abstract: This paper explores the impact of green credit policies on the environmental, social, and governance (ESG) performance of A-share listed companies in China through empirical analysis, with a particular focus on their effects on highly polluting industries. Based on data from A-share listed companies in China between 2010 and 2020, a multi-period difference-in-differences model was employed to analyze the differentiated effects of green credit policies across different regions and industries. The study found that green credit significantly improved companies' ESG ratings, especially in highly polluting industries, where its positive incentive effects were more pronounced. Robustness tests further confirmed the reliability of the research conclusions. As an important tool for guiding companies towards environmental transformation, green credit policies should be strengthened to promote corporate environmental technology upgrades. At the same time, the ESG rating system should be improved by establishing unified standards to enhance the objectivity and consistency of rating results.

Keywords: Green credit, corporate ESG performance, Difference-in-differences model, Robustness test.

1. Introduction

Amid the intensifying global climate change and increasing pressure on resources and the environment, governments worldwide are seeking to drive corporate green development transformation through economic policies. President Xi Jinping emphasized that "green development is the underlying tone of high-quality development, and the new type of productivity is inherently green productivity. We must accelerate the green transformation of development methods to support the achievement of carbon peaking and carbon neutrality." At present, China has established a multi-tiered green finance market system, centered on green loans and green bonds, with various green financial instruments thriving. Both domestic and foreign currency balances of green loans and green bonds rank among the highest globally. Green credit, as a policy that guides capital towards environmentally friendly projects through financial instruments, has become a key strategy for achieving sustainable development goals.

How can finance serve the green transformation of the economy and society? By vigorously developing green finance and providing more green financial products, traditional industries can be forced to transition toward low-carbon, green development, promoting the application and dissemination of green technologies. This will drive the real economy's green transformation,

contributing to the construction of ecological civilization and the realization of China's "dual carbon" goals. To mitigate credit risks arising from environmental violations by enterprises, protect the environment, and promote the development of a resource-saving and environmentally friendly society, the Chinese government issued the "Opinions on Implementing Environmental Protection Policies and Regulations to Prevent Credit Risks" in 2007. This strengthened environmental supervision and credit management for both new projects and existing enterprises, established a coordination mechanism between environmental protection and financial sectors, and reinforced the supervision of environmental and financial institutions to ensure effective policy implementation. Additionally, proactive responses from local governments further propelled the implementation of green credit policies. Over 20 provinces and cities, including Jiangsu, Zhejiang, and Henan, successively introduced specific green credit implementation plans. According to the National Bureau of Statistics, in 2007, the five major state-owned banks in China granted loans totaling 106.334 billion yuan to support key projects aimed at energy conservation and emission reduction, highlighting green credit as an effective tool for promoting corporate environmental investment and enhancing sustainable development capacity. The gradual promotion of green credit policies in China, particularly in high-pollution and high-energy-consuming industries, has had a significant impact on companies' environmental, social, and governance (ESG) performance.

Research indicates that green credit policies can effectively push companies to optimize their resource allocation and shift towards more environmentally friendly production methods. For instance, Ma et al. [1] found that green credit policies significantly increased energy efficiency, especially in eastern China. Moreover, green credit policies have profoundly affected the financing behavior and sustainable development performance of highly polluting enterprises. The study by Ke and Lu [2] shows that green credit can significantly enhance technological innovation capabilities in the manufacturing sector, particularly in the "two highs and one cyclical" industries (high pollution, high energy consumption, and cyclical industries). Furthermore, these policies have prompted banks and other financial institutions to place greater emphasis on companies' environmental records and sustainable development capabilities when evaluating loan applications, thereby fostering industry-wide movement towards environmentally friendly and sustainable development.

However, previous research has paid relatively little attention to how green credit policies comprehensively affect corporate ESG performance. To expand the scope of the literature, this study aims to explore the application effects of green credit policies in China's A-share listed companies, particularly their impact on the environmental, social, and governance (ESG) performance of companies in highly polluting industries. The study collected data from 3,674 A-share listed companies in China, covering 30,052 annual firm-level observations from 2010 to 2020. To precisely assess the long-term impact of green credit policies on corporate ESG ratings, a multi-period difference-in-differences (DID) model was constructed, allowing for an accurate capture of the effects of policy changes on corporate ESG performance.

Through detailed data analysis, this study found that after the implementation of green credit policies, corporate ESG ratings significantly improved, with the effect being particularly pronounced in highly polluting industries. This suggests that green credit policies not only alleviated companies' financial pressures but also incentivized them to strengthen their environmental protection efforts and social responsibility, thereby promoting an overall improvement in corporate ESG performance. Additionally, this study examined the differentiated effects of green credit policies across different regions and industries, revealing that regional economic development levels and industry characteristics may influence policy outcomes.

To ensure the robustness of the results, a series of robustness checks were conducted, including the use of alternative model specifications and substitute dependent variables. The results consistently supported the validity of the main conclusions. The study demonstrates that green credit policies exert

significant constraints and incentivizing effects on the environmental investment decisions of capital-intensive and highly polluting industries, effectively promoting companies' long-term commitments and investments in environmental protection and sustainable development. In this way, green credit policies provide strong policy support for promoting corporate sustainable development and achieving broader environmental goals.

This study makes significant contributions in the following aspects:

First, the research perspective is innovative. While most existing literature focuses on the impact of green credit on corporate environmental technology innovation and financing costs, this study reveals the comprehensive effects of green credit on corporate environmental, social, and governance (ESG) performance through empirical analysis, especially its differentiated effects on highly polluting industries. This provides a new research perspective for the design of green financial policies and enriches the research on how green credit influences corporate behavior and market reactions.

Second, the conclusions are also novel. Through empirical analysis, this study finds that green credit policies not only significantly improve corporate ESG ratings, but the incentive effects of these policies are particularly strong in highly polluting industries. This conclusion goes beyond previous research that focused solely on the impact of green credit on environmental technology innovation, revealing the long-term effects of these policies on the overall sustainable development capacity of firms.

Finally, this research has important policy implications. By uncovering the key role of green credit policies in promoting corporate ESG performance, this study provides empirical evidence for governments and financial institutions to optimize green financial policies. Particularly for companies in high-pollution, high-energy consumption industries, green credit policies can effectively guide their investment in environmental protection technologies and sustainable development decisions, thus reducing their negative environmental impacts.

The structure of this paper can be divided into the following main sections: (1) Literature Review: summarizing the effects of green credit on corporate ESG ratings and the views of various researchers; (2) Data Sources and Sample Description: introducing the dataset, sample criteria, and processing methods; (3) Variable Definition and Model Design: explaining the core variables and statistical models, and presenting descriptive statistical results; (4) Baseline Regression Analysis: analyzing the impact of green credit on ESG ratings through regression models; (5) Discussion and Conclusion: summarizing key findings, discussing policy implications, and outlining future research directions.

2. Literature Review

Green credit has emerged as a critical instrument in the financial sector, designed to promote sustainable business practices by providing favorable financing for environmentally friendly projects. Lei, Miao, and Yao [3] observed that the implementation of green credit policies has significantly impacted the ESG (Environmental, Social, and Governance) performance of companies in China, especially those listed on the A-share market. Their study found that green credit policies eased financial constraints and improved investment efficiency, particularly in state-owned enterprises, leading to enhanced environmental and social outcomes. Similarly, Lin [4] examined the effects of green credit in high-energy-consuming industries, noting that while it encourages green innovation, it also imposes financial burdens due to the costs associated with adopting new technologies. However, the effectiveness of green credit varies widely depending on regional and economic conditions. For instance, Li [5] revealed that its impact on ecological efficiency differed across Chinese provinces, becoming more pronounced in regions with higher initial ecological standards after 2015.

In the broader context of ESG criteria, research has increasingly sought to understand the factors influencing corporate sustainability. Liu and Hu [6] studied the role of financial technology (FinTech) in enhancing ESG performance. They concluded that FinTech significantly improved the efficiency of credit resource allocation and risk management, benefiting non-state-owned and smaller enterprises in particular. Zhen and Sun [7], on the other hand, explored the impact of discrepancies in ESG ratings on corporate green innovation. Their findings indicated that significant differences in ESG ratings often hinder green innovation by increasing financial constraints and reducing investment in research and development. In contrast, Lu and Gong [8] investigated the relationship between ESG and credit ratings, discovering a strong positive correlation. Their study concluded that higher ESG ratings could improve credit ratings, serving as a useful predictive tool for credit risk. Collectively, these studies underscore the importance of ESG criteria for sustainability assessments, though external factors such as technological advances and inconsistencies in rating practices also play a role in shaping their effectiveness.

The relationship between green credit and ESG criteria is multifaceted and shaped by various contextual factors. Lei, Miao, and Yao [3] demonstrated that green credit policies directly enhance ESG performance by incentivizing companies to adopt environmentally and socially responsible practices. This positive influence is further supported by Qing [9], who noted that green credit is especially effective for non-state-owned enterprises that face challenges accessing traditional financing. However, the benefits of green credit are not evenly distributed. Rong and Hu [9] emphasized that while green credit policies help reduce social health costs, their impact is significantly more pronounced in regions with better initial conditions, such as eastern China. Furthermore, Ma et al. [10] argued that the positive effects of green credit on energy efficiency and ESG performance are contingent upon robust financial regulation and market maturity. Thus, while green credit can be a powerful driver of ESG improvements, its effectiveness is highly dependent on the regulatory and economic environment, underscoring the importance of well-crafted policies tailored to local conditions.

3. Data Source, Model, and Statistical Analysis

3.1. Sample and Data Source

The data used in this study is sourced from the China Stock Market & Accounting Research (CSMAR) database. The dataset includes information on Chinese A-share listed companies from 2010 to 2020, covering 3,674 companies with a total of 30,052 observations. The data consists of variables such as financial information, ESG ratings, and regional distribution, spanning a ten-year period. This extended timeframe effectively captures the long-term dynamic impact of green credit policies on companies' ESG ratings. Additionally, the sample companies are distributed across 31 provinces, providing strong regional representativeness and reflecting the varied effects of green credit policy implementation across different regions in China.

During data processing, several rigorous steps were undertaken to ensure the scientific validity and reliability of the data. First, with regard to ESG ratings, four mainstream ESG rating systems were adopted: Huazheng ESG Ratings, Wind ESG Ratings, SynTao Green Finance ESG Ratings, and SusallWave ESG Ratings. These four systems have high recognition and influence in China's capital market. However, due to differences in scoring standards and methods among the rating agencies, each rating was standardized into a uniform scale, where each level corresponds to a specific score. Second, regional variables were classified and assigned appropriate values. To examine the regional differences in the impact of green credit policies and control for the heterogeneity of regional economic development levels, this study classified companies based on China's traditional division into the eastern, central, and western regions. For the purpose of quantitative analysis, the eastern,

central, and western regions were assigned values of 0, 1, and 2, respectively. This approach not only helps control for regional fixed effects in the regression analysis but also clearly demonstrates the differential impacts of green credit policies across regions. Finally, since some companies may have missing ESG ratings or financial data in certain years, directly eliminating missing values could significantly reduce the sample size and affect the generalizability of the results. Therefore, companies were grouped by stock codes, and the average values of each variable within each group were calculated and used to fill in the missing values.

3.2. Variable Definitions

3.2.1. Explanatory Variables

The explanatory variables include two core variables: treat and post, which measure whether a company belongs to a high-pollution industry and whether it falls within the time period of green credit policy implementation.

The treat variable identifies whether a company operates in a heavy industry or high-energy-consuming sector. If the company is in industries such as electricity or coal, which are characterized by high pollution and energy consumption, the variable is assigned a value of 1; otherwise, it is 0.

The post variable indicates whether the company is evaluated after the implementation of green credit policies. Since China's green credit policy was introduced in 2012, if the company's ESG rating year is 2012 or later, the post variable takes the value of 1; otherwise, it is 0.

3.2.2. Dependent Variable

The interaction variable is the interaction term between treat and post, representing companies that are both in high-pollution industries (treat=1) and evaluated after the green credit policy was implemented (post=1). This variable is used to assess the impact of green credit policies on the ESG ratings of companies in high-pollution industries.

3.2.3. Control Variables

To ensure the accuracy of the regression results and avoid omitted variable bias, a series of control variables were introduced. These variables were selected based on existing economic theories and literature, providing strong support for the regression analysis. They cover key financial indicators such as company size, profitability, and asset structure, and include the following variables:

- Company size (Size)
- Growth rate of main business revenue (SG1)
- Operating profit (OProfit)
- Earnings before interest and taxes (EBIT)
- Net income (NI)
- Cash flow from operating activities (OCF)
- Return on assets (ROA)
- Tangibility of assets (Tangibility)
- Cash ratio (Cash)
- Tobin's Q ratio (tobinqA)

These control variables encompass multiple aspects of a company's financial performance, profitability, and asset structure, aiming to comprehensively account for the impact of company characteristics on ESG ratings. This ensures that the estimated effects of green credit policies are more accurate and robust.

3.3. Model Design

This study adopts a multi-period difference-in-differences (DID) model with fixed effects to analyze the impact of green credit policies on corporate ESG ratings. The specific model is set as follows:

$$ESG_{i,t} = \beta_0 + \beta_1 GI_j + \beta_2 Post_t + \beta_3 GI_j \times Post_t + \Gamma X_{i,t} + \epsilon_{i,t} \quad (1)$$

Where the dependent variable ESG represents the ESG rating of company i in year t , primarily measuring the company's overall performance in environmental, social, and governance aspects. GI_j is a dummy variable indicating whether the company belongs to a heavily polluting, high-energy-consuming industry significantly impacted by green credit. $Post_t$ is a dummy variable representing the time of green credit policy implementation. If the ESG rating year t is later than 2012, $Post_t = 1$; otherwise, $Post_t = 0$. The interaction term $GI_j \times Post_t$ is the key explanatory variable, reflecting the differential impact of green credit policies on heavily polluting firms. The regression coefficient β_3 captures the net effect of the green credit policy on the ESG ratings of companies in high-pollution industries. If β_3 is positive, it indicates that the policy has a positive incentivizing effect on the ESG ratings of these companies. $\Gamma X_{i,t}$ is the matrix of firm-level control variables, as discussed in the previous section. $\epsilon_{i,t}$ is a random disturbance term capturing unexplained random factors in the model.

When estimating the model, time and regional fixed effects are included to control for potential heterogeneity across years and regions, eliminating systematic influences on ESG ratings caused by different years and regions. Furthermore, the standard errors in the model are clustered at the firm level to address potential heteroskedasticity and autocorrelation issues in the error terms, thus improving the robustness of the model's estimation.

3.4. Descriptive Statistics

Table 1: Summary Statistics.

VarName	Obs	Mean	SD	Min	Max
esg	29211	4.108	1.089	1.000	8.000
esg1	9815	3.398	0.844	1.000	7.000
esg2	3371	5.110	0.949	3.000	8.000
esg3	2024	8.556	3.473	2.000	18.000
treat	30014	0.042	0.200	0.000	1.000
post	30052	0.794	0.405	0.000	1.000
interaction	30014	0.033	0.177	0.000	1.000
Size	30052	22.119	1.321	15.577	28.636
SG1	26847	5.927	826.615	-2.733	1.35e+05
OProfit	30052	6.43e+08	4.11e+09	-1.85e+10	1.93e+11
EBIT	30052	0.044	0.102	-4.865	0.787
NI	30052	5.23e+08	3.21e+09	-1.82e+10	1.51e+11
OCF	30052	0.619	0.587	0.000	13.455
ROA	30052	0.034	0.098	-4.946	0.786
Tangibility	30052	0.211	0.163	0.000	0.971
Cash	30052	2.06e+09	9.42e+09	0.000	6.28e+11
tobinqA	30052	2.155	2.859	0.153	259.146

Table 2 presents the descriptive statistics of the variables used in this study. Columns (1) to (5) respectively show the descriptive statistics for the variables in the sample, including the number of

observations, mean, standard deviation, minimum, and maximum values. The sample consists of A-share listed companies from 2010 to 2020, covering ESG ratings and related financial indicators. The descriptive statistics provide an initial understanding of the distribution characteristics of each variable, serving as a foundation for subsequent regression analysis.

The mean value of the ESG variable in the sample is 4.108, with a standard deviation of 1.089, a minimum of 1.000, and a maximum of 8.000. This suggests that there is some variation in the ESG ratings among companies in the sample, with most companies' ESG performance ranging from medium to high levels. esg1, esg2, and esg3 represent the ESG ratings from different rating agencies. As can be observed, there are some differences in the means and standard deviations across these rating systems.

The mean of the treat variable is 0.042, indicating that about 4.2% of the companies in the sample belong to high-pollution, high-energy-consuming industries, and the ESG ratings of these companies may be significantly affected by green credit policies. The mean of the post variable is 0.794, showing that nearly 80% of the sample companies are in the period after the implementation of green credit policies, providing a sufficient sample basis for analyzing the policy effects.

Overall, the descriptive statistics in Table 2 reveal some variability in companies' ESG ratings, particularly across different rating systems and industry classifications. This offers sufficient background support for further exploration of the impact of green credit policies on corporate ESG ratings.

4. Baseline Regression Analysis

Table 2: Baseline Regression: The Impact of Green Credit on Corporate ESG.

VARIABLES	(1)	(2)	(3)	(4)
	esg	esg	esg	esg
treat	-0.170** (0.068)	-0.448*** (0.084)	-0.449*** (0.084)	-0.454*** (0.088)
post	-0.069*** (0.016)	-0.136*** (0.019)	-	-
interaction	0.193** (0.077)	0.312*** (0.090)	0.314*** (0.090)	0.359*** (0.094)
Size		0.170*** (0.006)	0.174*** (0.006)	0.176*** (0.006)
SG1		-0.000* (0.000)	-0.000* (0.000)	-0.000* (0.000)
OProfit		-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
EBIT		4.554*** (0.712)	4.384*** (0.711)	4.378*** (0.725)
NI		0.000 (0.000)	0.000* (0.000)	0.000 (0.000)
OCF		-0.032*** (0.011)	-0.036*** (0.011)	-0.048*** (0.011)
ROA		-2.533*** (0.754)	-2.329*** (0.753)	-2.355*** (0.767)
Tangibility		-0.343*** (0.042)	-0.340*** (0.042)	-0.275*** (0.044)

Table 2: (continued).

Cash		0.000	0.000	0.000
		(0.000)	(0.000)	(0.000)
tobinqA		-0.020***	-0.016***	-0.016***
		(0.002)	(0.002)	(0.002)
Constant	4.163***	0.462***	0.319**	0.322**
	(0.014)	(0.134)	(0.135)	(0.138)
Baseline Regression Control Variables	Not controlled	Controlled	Controlled	Controlled
Year Fixed Effects	Not controlled	Not controlled	Controlled	Controlled
Region Fixed Effects	Not controlled	Not controlled	Not controlled	Controlled
Observations	29,173	26,060	26,060	24,879
R-squared	0.001	0.094	0.099	0.102

4.1. Model Specification

This paper analyzes the impact of green credit policies on the environmental, social, and governance (ESG) ratings of enterprises through four regression models. As the model specification progresses, control variables and fixed effects are gradually introduced to improve the accuracy and explanatory power of the regression results.

First, Model (1) includes only the core explanatory variables without controlling for any other factors. This model primarily examines the direct effects of three core variables on corporate ESG ratings: treat (whether the enterprise belongs to a high-pollution, high-energy-consuming industry), post (the period after the implementation of green credit policies), and interaction (the interaction term between treat and post). This model serves as the baseline model, initially revealing the direction and significance of the impact of green credit policies on corporate ESG ratings. Subsequently, Model (2) introduces several enterprise-level control variables, such as enterprise size (Size), growth rate of main business revenue (SG1), and operating profit (OProfit). Controlling for these factors helps eliminate the confounding effects of differences in enterprise characteristics on ESG ratings, thereby improving the accuracy of the regression results. Next, Model (3) adds year fixed effects. Year fixed effects can control for macroeconomic fluctuations, policy changes, and other time-varying factors that may influence the regression results, thus better isolating the effects of green credit policies.

Finally, Model (4) further introduces regional fixed effects based on the previous models. The inclusion of regional fixed effects aims to control for the impact of differences in policy enforcement intensity and environmental governance requirements across regions on corporate ESG ratings, ensuring the stability and universality of the regression results.

4.2. Statistical Significance of Regression Coefficients and Their Implications

When analyzing the regression results of the models, the regression coefficients of the core variables treat, post, and interaction are particularly crucial, as the significance and signs of these variables directly reflect the impact of green credit policies on corporate ESG ratings.

4.2.1. Treat (High Pollution, High Energy Consumption Enterprises)

The treat variable measures whether an enterprise belongs to a high-pollution, high-energy-consuming industry, including sectors such as electricity, coal, oil, and natural gas extraction. The regression results show that the coefficient of the treat variable is negative across all four models and

is significant at the 1% or 5% significance level. Specifically, the regression coefficient of the treat variable in Model (1) is -0.170, while in other models, it ranges from -0.448 to -0.454. These results indicate that the ESG ratings of high-pollution enterprises are significantly lower than those of other enterprises.

This finding suggests that enterprises in high-pollution and high-energy-consuming industries face greater environmental governance pressures and higher challenges for sustainable development, leading to poorer performance in the ESG rating system. The production models of high-pollution enterprises have a substantial impact on the environment, resulting in lower environmental ratings, which in turn affects their overall ESG ratings.

4.2.2. Post (After the Implementation of Green Credit Policies)

The post variable represents the time period after the implementation of green credit policies. The regression results indicate that the post variable has negative coefficients in Models (1) and (2), at -0.069 and -0.136 respectively, both significant at the 1% significance level. This suggests that after the implementation of green credit policies, the overall ESG ratings of enterprises have declined. This finding may reflect the challenges enterprises face in adapting to new regulatory requirements in the early stages of policy implementation. The policy requires enterprises to invest more in environmental governance, but their short-term responsiveness is limited, leading to a decline in ESG ratings during the early stages of policy implementation.

4.2.3. Interaction (Interaction Term Between Post and Treat)

The interaction variable measures the specific impact of green credit policies on high-pollution enterprises after their implementation. The regression coefficients of this variable are positive and significant in all models, with a coefficient of ****0.193**** in Model (1), rising to ****0.359**** in Model (4), both significant at the 1% or 5% significance level. The results indicate that although high-pollution enterprises had lower ESG ratings before the implementation of green credit policies, the improvement in their ratings after policy implementation is significantly greater than that of other enterprises. Green credit policies impose stronger incentives and constraints on high-pollution enterprises, prompting them to place greater emphasis on environmental governance and sustainable development. This also indicates that the impact of policies on high-pollution enterprises is more significant, successfully promoting progress in these enterprises' ESG ratings.

4.3. Influence of Other Control Variables

In addition to the core explanatory variables, the regression models also introduce multiple enterprise characteristic variables to more comprehensively assess the impact of green credit policies. These control variables show significant regression coefficients across different models, providing additional dimensions for the research.

4.3.1. Size (Enterprise Size)

The enterprise size exhibits a positive and significant influence across all models, with coefficients ranging from 0.170 to 0.176. This indicates that larger enterprises perform better in ESG ratings. Large enterprises typically have more resources for environmental protection and social responsibility initiatives, and their scale effect enables them to respond more effectively to regulatory requirements. Moreover, the heightened scrutiny from the public and regulatory bodies on large enterprises compels them to act more proactively and transparently in the ESG domain.

4.3.2. EBIT (Earnings Before Interest and Taxes)

The regression coefficients for the EBIT variable are positive and significant across all models, ranging from 4.378 to 4.554 at the 1% significance level. This suggests that highly profitable enterprises have an advantage in ESG ratings. This may be attributed to the fact that profitable enterprises can afford to invest more in environmental initiatives and social responsibility activities, thereby enhancing their ESG performance. Financially healthy enterprises are not only able to meet investors' expectations for financial returns but also capable of assuming greater sustainable development responsibilities.

4.3.3. ROA (Return on Assets)

The ROA variable shows negative and significant coefficients across all models, with a range from -2.329 to -2.533. This indicates that enterprises with higher return on assets actually tend to have lower ESG ratings. This finding may be related to enterprises being overly focused on short-term financial performance. In the pursuit of high returns, enterprises may neglect long-term investments in environmental protection and social responsibility, leading to poorer ESG performance. This suggests that there may be a trade-off between high financial returns and strong ESG performance.

4.4. Brief Summary

Through the above regression analysis, we find that the impact of green credit policies on corporate ESG ratings exhibits significant variability. High-pollution enterprises have lower ESG ratings before the implementation of the policies, but their ratings improve significantly after the policies are enacted. This indicates that green credit policies have a marked constraining and incentivizing effect on specific industries. Additionally, enterprise characteristics such as size, profitability, and the proportion of tangible assets significantly influence corporate ESG ratings. In summary, the implementation of green credit policies effectively promotes sustainable development in high-pollution industries, but the internal characteristics of enterprises also play a crucial role in their ESG performance.

5. Robustness Check

Table 3: Robustness Check Results.

	(1)	(2)	(3)	(4)	(5)	(6)
	Stability Test for Changing Sample Interval	Robustness Test for Changing ESG Definition			Robustness Test for Removing Outliers	Heteroscedasticity Robust Standard Errors
VARIABLES	esg	esg1	esg2	esg3	esgnew	esg
treat	-0.423*** (0.086)	-0.251*** (0.048)	-0.232*** (0.064)	-0.448* (0.241)	-0.418*** (0.083)	-0.454*** (0.084)
interaction	0.343*** (0.093)				0.355*** (0.088)	0.359*** (0.091)
Size	0.169*** (0.007)	0.034*** (0.008)	0.166*** (0.019)	1.481*** (0.071)	0.166*** (0.006)	0.176*** (0.007)
SG1	-0.000* (0.000)	-0.004** (0.002)	-0.042 (0.031)	-0.189 (0.177)	-0.000* (0.000)	-0.000*** (0.000)
OProfit	-0.000 (0.000)	-0.000** (0.000)	-0.000** (0.000)	-0.000*** (0.000)	-0.000 (0.000)	-0.000 (0.000)

Table 3: (continued).

EBIT	3.995***	-4.364***	-6.600***	6.316	4.526***	4.378***
	(0.769)	(0.857)	(1.728)	(6.478)	(0.681)	(1.127)
NI	0.000	0.000***	0.000**	0.000***	0.000	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
OCF	-0.048***	-0.041***	0.010	0.296***	-0.048***	-0.048***
	(0.012)	(0.015)	(0.031)	(0.113)	(0.011)	(0.012)
ROA	-2.041**	5.200***	7.183***	1.574	-2.731***	-2.355*
	(0.816)	(0.890)	(1.859)	(6.945)	(0.720)	(1.283)
Tangibility	-0.304***	0.344***	0.665***	1.251***	-0.267***	-0.275***
	(0.046)	(0.059)	(0.103)	(0.387)	(0.042)	(0.045)
Cash	0.000*	-0.000	-0.000***	-0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
tobinqA	-0.017***	0.026***	0.017*	0.270***	-0.015***	-0.016**
	(0.003)	(0.006)	(0.010)	(0.035)	(0.002)	(0.006)
Constant	0.491***	2.514***	0.730	-27.413***	0.550***	0.322**
	(0.147)	(0.174)	(0.458)	(1.717)	(0.130)	(0.163)
Baseline Regression Control Variables	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
Year Fixed Effects	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
Region Fixed Effects	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
Observations	21,646	9,402	3,223	1,939	24,879	24,879
R-squared	0.101	0.054	0.104	0.423	0.102	0.102

To ensure the reliability and robustness of the research findings, we conducted various robustness tests on the impact of green credit policy on corporate ESG ratings. Since different sample intervals, rating criteria, and data anomalies may affect the regression results, robustness tests help to verify whether the research conclusions have broad applicability. By adjusting the sample intervals, using different ESG rating standards, removing outliers, and employing heteroscedasticity-robust standard errors, we aim to eliminate potential external factors that could interfere with the regression results, thereby ensuring that the conclusions regarding the impact of green credit policy on corporate ESG ratings are robust.

5.1. Robustness Test of Changing Sample Interval

The pandemic has had a widespread impact on the global economy, causing many companies to adjust their financial performance, operational methods, and ESG strategies. Therefore, to avoid the interference of short-term shocks caused by the pandemic on the regression results, this paper chooses to adjust the sample interval to before 2020, excluding data from pandemic-related years, to more accurately reflect the impact of green credit policy on corporate ESG ratings under normal economic conditions.

By changing the time period for firms entering the sample, we re-ran the regression for the core variables. The results showed that the coefficient for the treat variable is -0.423, which is significant at the 1% level, indicating that the ESG ratings of high-pollution companies are significantly lower

than those of other companies. At the same time, the coefficient for the interaction variable is 0.343, significantly positive, indicating that after the policy implementation, the ESG ratings of high-pollution companies improved substantially. This result suggests that despite the change in sample interval excluding the impact of the pandemic, the overall impact of green credit policy on corporate ESG ratings remains significant and has not undergone significant change due to the adjustment of the sample interval.

5.2. Changing ESG Rating Standards

When studying the impact of green credit policy on corporate ESG ratings, different ESG rating standards may lead to biases and inconsistencies in the results. The formulation of ESG rating standards often relies on different indicator systems and evaluation methods, with variations in weight allocation and data processing across rating agencies. Therefore, to ensure the robustness and universality of the research conclusions, it is necessary to conduct robustness tests using multiple ESG rating standards. This paper selects three mainstream ESG rating systems: Wind, SynTao Green, and SusallWave for comparative analysis, aiming to verify whether the impact of green credit policy on corporate ESG performance remains consistent across different rating systems. This test helps to enhance the generalizability of the research conclusions and reduces biases arising from differences in rating standards.

① Robustness Test of Wind ESG Rating

To ensure that the results do not depend on specific ESG rating standards, this paper employs the Wind ESG rating as an alternative indicator. The coefficient for the treat variable is -0.251, significantly negative, indicating that when using the Wind ESG rating, the ESG ratings of high-pollution companies remain low. Additionally, other control variables, such as Size (coefficient 0.034), continue to have a significant impact on ESG ratings.

② Robustness Test of SynTao Green ESG Rating

When conducting robustness tests using the SynTao Green ESG rating system, the coefficient for the treat variable is -0.232, significantly negative ($p < 0.01$), further confirming that high-pollution companies continue to perform poorly in ESG ratings under this rating system. Meanwhile, the coefficient for the Size variable is 0.166, significantly positive, indicating that company size continues to have a positive influence on ESG ratings.

③ Robustness Test of SusallWave ESG Rating

This paper uses the SusallWave ESG rating standard for further robustness testing. In this model, the coefficient for the treat variable is -0.448, significantly negative at the 10% significance level, indicating that even under this ESG rating, the ESG ratings of high-pollution companies remain low. EBIT (coefficient 6.316) shows a strong positive effect, while variables such as SG1 are not significant.

The results show that the core regression coefficients remain consistent across different rating systems, indicating that the impact of green credit policy on corporate ESG performance does not significantly fluctuate due to changes in rating standards. Despite differences in specific evaluation methods among rating systems, the direction and degree of the policy's impact on high-pollution companies remain robust. Therefore, it is evident that the effects of green credit policy exhibit high consistency across different ESG rating standards, further supporting the credibility of the research conclusions.

5.3. Robustness Test by Removing Outliers

In regression analysis, outliers can significantly bias the results, leading to reduced explanatory power of the model or conclusions that deviate from reality. To enhance the accuracy and robustness of the

model results, it is necessary to address outliers. This study tests whether the policy's impact on corporate ESG ratings remains significant by restricting the data to the 5%-95% range.

After removing the outliers from the sample, a new regression analysis was conducted, and the results indicate that the influence of core variables remains robust. The coefficient for the treat variable is -0.418, significantly negative at the 1% significance level, indicating that the ESG ratings of highly polluting enterprises are significantly lower than those of other enterprises. Following the implementation of the policy, the coefficient for the interaction variable is 0.355, significantly positive, suggesting that the positive impact of the policy on highly polluting enterprises still exists. Additionally, the regression coefficients for control variables, such as Size and ROA, align with those from the baseline model, indicating that the influence of these variables has not significantly changed due to the removal of outliers.

This robustness test demonstrates that the impact of outliers on regression results is minimal, and the significance and directionality of core variables have not changed significantly. The negative impact of green credit policies on the ESG ratings of highly polluting enterprises, as well as the positive improvement effect following policy implementation, remains valid even after the removal of outliers, further validating the robustness of the research conclusions. This suggests that the research findings have not been severely disrupted by extreme data, indicating a high level of reliability.

5.4. Heteroskedasticity Robust Standard Error Test

Considering the potential heteroskedasticity issues in the model, this study re-estimated the regression results using heteroskedasticity-robust standard errors. The coefficient for the treat variable is -0.454, significantly negative at the 1% significance level, and the coefficient for the interaction variable is 0.359, still significantly positive. This indicates that even when accounting for heteroskedasticity issues, the policy's impact on highly polluting enterprises remains significant. Moreover, the coefficients for control variables, such as enterprise size and profitability, also remain stable.

The regression results using heteroskedasticity-robust standard errors suggest that the impact of heteroskedasticity issues on the regression model is minor, and the negative impact of green credit policies on highly polluting enterprises, as well as the positive incentivizing effect post-implementation, remains solid. The results for the control variables also show a high degree of consistency, further validating the robustness and reliability of the regression conclusions.

6. Conclusion

In promoting corporate sustainable development and environmental governance, green finance, especially green credit policies, has become an important tool for governments and financial institutions to guide enterprises towards low-carbon and environmentally friendly transformations. As national requirements for environmental protection have increased, green credit policies have gradually become a significant criterion for enterprises to obtain financing, particularly for high-pollution and high-energy-consuming industries. By introducing green credit policies, governments and financial institutions can effectively direct funding towards enterprises with good environmental and social responsibility performance, thereby achieving coordinated development between the environment and the economy. Based on ESG rating data from Chinese A-share listed companies from 2010 to 2020, this study employs a difference-in-differences model to investigate the impact of green credit policies on corporate ESG performance. The results show that green credit policies have a significant positive impact on corporate ESG ratings, especially in high-pollution and high-energy-consuming industries. The above results remain valid after robustness tests.

6.1. Policy Recommendations

6.1.1. Increase Green Credit Support for High-Pollution Industries

High-pollution industries play a significant role in economic development, but their production processes often lead to considerable environmental pollution and energy consumption. Through green financial measures, these enterprises can be effectively guided to invest in environmental technology upgrades and clean energy, thereby reducing their negative impact on the environment. First, it is essential to establish a dedicated green financial support mechanism. Special green credit funds should be set up for high-pollution industries, specifically aimed at supporting enterprises in energy conservation, emission reduction, upgrading environmental protection equipment, and transforming clean production technologies. Financial institutions can lower the financing costs for high-pollution enterprises through differentiated loan interest rates or by issuing green bonds, while also providing long-term, low-interest green loans to help these enterprises secure stable funding for their long-term investments in environmental protection. Secondly, it is crucial to improve policy incentive measures to promote green technology innovation. The government can introduce green financial incentive policies specifically for high-pollution industries, offering subsidies, tax reductions, and other measures to encourage enterprises to invest funds into the research and application of environmental protection technologies. By establishing a green technology innovation fund, the government and financial institutions can jointly support enterprises in achieving technological breakthroughs, thereby enhancing their competitiveness in environmental protection and creating a virtuous cycle of environmental governance and enterprise growth.

6.1.2. Promote and Improve the ESG Rating System

With the in-depth development of green credit and sustainable finance, ESG (Environmental, Social, and Governance) ratings have become important indicators for measuring corporate sustainable development performance. However, the current ESG rating standards are inconsistent, and the disclosure of corporate information is inadequate, which may affect the decision-making of financial institutions and investors. Therefore, improving and promoting the ESG rating system is crucial for advancing green finance. First, a unified ESG rating standard should be established. Currently, there are significant differences in the evaluation criteria of corporate ESG performance among various rating agencies in the market, leading to considerable score disparities for the same enterprise across different ratings. It is recommended that the government or industry associations take the lead in formulating a unified ESG rating standard, covering multiple dimensions such as environmental protection, social responsibility, and corporate governance, while clearly defining the weight of each criterion to ensure the objectivity and consistency of the rating results.

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