Transactions on Economics, Business and Management Research
ISSN: 2960-1789, eISSN: 2960-2254 | Volume 11
EMFT 2024

Impact of Green Credit Policies on Green innovation in Low-Pollution Industries

Jiaxin Guo *

College of Economics and Management, China Agricultural University, Beijing, China, 100083

* Corresponding Author Email: jiaxin.guo@cau.edu.cn

Abstract. This paper addresses the fundamental role of green innovation (GI) in tackling environmental pollution and carbon emissions, emphasizing the pivotal role of green credit policy (GCP) in the market-driven allocation of GI resources. Historically, green credit (GC) has predominantly targeted high-pollution industries (HPI), often neglecting low-pollution industries (LPI). As the scale of GC in HPI stabilizes, the growth rate of their GI is expected to decelerate, highlighting LPI as potential key areas for GC and GI. Utilizing the 2016 "Guiding Opinions on Building a Green Financial System" as a quasi-natural experiment, this study employs a difference-in-differences model to assess the impact of GCP on GI in LPI. The findings reveal a significant improvement in GI in LPI post-implementation of the "Guiding Opinions," compared to ordinary industries. However, challenges such as quantity improvement without quality enhancement and innovation lag remain. This study makes two key contributions. Firstly, it re-evaluates the impact of GCP on GI in HPI by excluding green environmental protection enterprises (GEPE) and HPI enterprises. Secondly, it fills the research gap regarding the impact of GCP on LPI.

Keywords: Green Credit Policy, Green innovation, low-pollution, Difference-in-Differences (DID).

1. Introduction

GI are essential solutions to environmental pollution and carbon emissions. Unlike traditional technological innovation, GI is characterized by long cycles, slow returns, difficult evaluation, and high risks [1].The current challenge in GI is the high cost of green products and services. This lack of price advantages leads to a heavy reliance on financial subsidies for many GEPE [2] . This reliance, coupled with frequent subsidy fraud, further constrains enterprises' ability to independently innovate [3], making it difficult to achieve market-based allocation in the green industry.

To significantly improve GI, it is necessary to use green financial mechanisms to change the incentive structure for resource allocation [4]. China has been continuously exploring green financial policies. In 2012, the former China Banking Regulatory Commission formulated the "Green Credit Guidelines" ("Guidelines"), and in 2016, seven departments, including the People's Bank of China, issued the "Guiding Opinions on Building a Green Financial System" ("Guiding Opinions"). These measures aim to build and improve the green financial system, providing a valuable perspective for analyzing the role of green finance. Since 2016, the proportion of green credit balance (GCB) to the total scale of green financing in China has averaged 90%, suggesting that research conclusions based on GC can largely represent the role of green finance.

Previous GC activities focused on two key areas. From the perspective of pollution industries (PI), GCP promote GI primarily through "credit restrictions" and the environmental regulation costs they entail. Enterprises highly dependent on external financing are forced to innovate greenly due to long-term credit financing constraints [5].

From the perspective of GEPE, GCP promotes GI by "guiding effective market demand" and "relaxing liquidity constraints." GCP guide financial resources, such as bank and commercial credit, toward green sectors (According to the definition of green industries in the "Green Industry Guidance Catalog (2019 Edition)" (hereinafter referred to as the "Guidance Catalog") issued by seven ministries and commissions including the National Development and Reform Commission, companies whose main business belongs to energy conservation and environmental protection, clean production, clean energy, ecological environment, green infrastructure upgrading, and green services are defined as green enterprises.), strengthening market demand for green technologies and their products or services, thereby promoting GI [6].

Overall, existing literature has primarily focused on the promotion or inhibition effects of GCP on GI in HPI. Most studies have not excluded individual GEPE, potentially leading to a misestimation of policy effects due to the bidirectional nature of the "Guiding Opinions" (i.e., restricting loans to PI while supporting loans to GEPE). In practice, credit funds have mainly flowed to HPI enterprises (Category A enterprises The "Key Evaluation Indicators for the Implementation of GC" (Yin Jian Ban Fa [2014] No. 186) stipulates that classification standards should be established based on the environmental and social risks faced by clients, categorizing them into different groups. Category A refers to clients whose construction, production, and operational activities may severely alter the original environment and produce adverse environmental and social consequences that are difficult to mitigate. Category B refers to clients whose construction, production, and operational activities will produce adverse environmental and social consequences that can be more easily mitigated through remedial measures.)[7], with insufficient attention to LPI enterprises (Category B enterprises). This lack of focus has resulted in inadequate GI incentives for B enterprises. Empirical studies indicate that while the "Guidelines" significantly improved GI in HPI, their effect on LPI was negative but not significant [4]. This is also reflected in the annual average number of environmental penalties (Figure 1), where B enterprises sometimes faced more penalties than A enterprises, even experiencing extreme situations like smog index surges [8]. Therefore, B enterprises are a key focus for the future implementation of GCP. Moreover, related literature reveals that existing GCP face issues such as "credit discrimination," which can harm the total factor productivity of enterprises [9] . These policies need further adjustment.

In light of this, this paper uses the 2016 "Guiding Opinions" as a quasi-natural experiment to examine the effects of GCP on GI in LPI, employing a difference-in-differences (DID) approach. Specifically, the marginal contributions of this study are as follows:

(1) it re-evaluates the impact of GCP on GI in HPI by excluding green environmental protection enterprises and Category B enterprises;

(2) it fills the research gap regarding the impact of GCP on LPI.

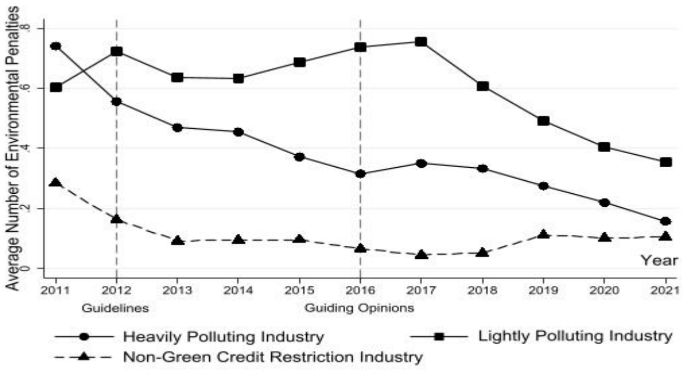

Figure 1. Average Number of Environmental Penalties.

2. Research Design and Descriptive Statistical Analysis

2.1. Difference-in-Differences (DID)

The DID model estimates causal relationships by comparing changes in outcomes over time between a treatment group and a control group. This method reduces the impact of unobserved heterogeneity, providing accurate policy effect estimates. Figure 2 illustrates the principle, showing changes in both groups before and after the intervention to identify the policy's actual impact.

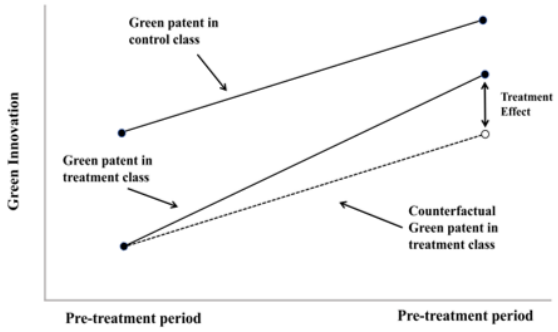

Figure 2. Difference-in-Difference Model.

2.2. Sample Selection and Data Sources

This study uses unbalanced panel data from 1,984 listed companies on the Shanghai and Shenzhen A-shares from 2011 to 2021.The data is preprocessed according to the following criteria:

(1) Excluding companies in the financial, insurance and green sectors. This study mainly examines the impact of GCP on GI from the perspective of polluting enterprises. Considering that GCP affect both polluting and green enterprises, including green enterprises in the control group would result in a misestimation of the effects[6].

(2) Excluding companies with abnormal operations during the sample period, such as those with a debt-to-asset ratio less than 0, greater than 1, or negative owner's equity.

(3) Excluding abnormally traded listed companies (including ST, ST*, and PT).

(4) Excluding listed companies with missing relevant data.

The data utilized in this study were sourced from several reputable platforms. Corporate innovation data, including patent classification numbers for invention and utility model patents of certain A-share listed companies, were acquired from the China Research Data Service Platform (CNRDS). These patents were subsequently matched with the "International Patent Classification Green List" published by the World Intellectual Property Organization (WIPO) in 2010. Based on this matching and relevant literature, the patents were categorized into green patents, encompassing green invention patents and green utility model patents, and non-green patents. In addition, other corporate characteristic data, primarily financial information, were obtained from the China Stock Market & Accounting Research (CSMAR) Database.

The data were matched, and the primary continuous variables were winsorized at the 1% and 98.5% levels. The final dataset consists of 12,150 observations from 1,180 companies, with 393 observations from HPI, 4,055 observations from LPI, and 7,702 observations from non-green-credit- restricted industries (ordinary industries).

2.3. Benchmark Model Framework and Variable Description

Based on the DID model, the following model was constructed to test the effect of GCP on GI:

$$P_{it+1} = \alpha_0 + \alpha_i + \alpha_t + \beta_0 Gcres_k + \beta_1 did_k + \beta_2 Policy + \gamma \chi_{it} + \varepsilon_{it} \tag{1}$$

The dependent variable P_{ikt+1} in Model (1) represents the GI performance of enterprise i in year (t+1). Referring to the methods of related literature[10], this paper uses green patent application data to represent GI. The total number of green patent applications (Total) and the number of green utility model patent applications (Uma) are used to measure the quantity of GI, while the number of green invention patent applications (Inva) is used to measure the quality of GI. Considering the skewed distribution of patent data, the natural logarithms of the application quantities plus one (LnTotal, LnInva, LnUma) are used.

The key explanatory variable $\mathrm{did_k}$ in Model (1) is the interaction term between industry attribute $\mathrm{Gcres_k}$ and GCP, where k can be A (HPI) or B (LPI). $\mathrm{Gcres_A}$ is a dummy variable, with 1 indicating that the enterprise belongs to the HPI and 0 indicating that it belongs to the control group (ordinary industries, excluding B industries). Similarly, $\mathrm{Gcres_B}$ is 1 if the enterprise belongs to the LPI, and 0 if it belongs to the ordinary industries (excluding A industries). $\mathrm{did_k}$ examines the impact of the "Guiding Opinions" before and after implementation on the GI of k industries compared to ordinary industries.

A series of control variables were introduced based on existing literature[11]. These include the proportion of institutional investor holdings (Inst), dual roles of chairman and CEO (Dual), proportion of independent directors (Ind), market-to-book ratio (Mtb), cash ratio (Cash), R&D expenditure ratio (Rd), debt-to-asset ratio (Debt), capital expenditure ratio (Capital), fixed asset ratio (Ppe), company performance (Roa), employee size (Employee), and company value (TQ) . The regression model controls for firm, time, and provincial fixed effects, using clustered standard errors at the firm level.

2.4. Descriptive Statistics

The descriptive statistics of the variables in this paper are shown in Table 1. The mean value of Total is 2.403, with a standard deviation of 7.032, indicating significant differences in the number of green patent applications among the sample enterprises. The lower quartile (p25) and the median of green patent applications are both 0, suggesting that most enterprises did not engage in GI. The mean values of Inva and Uma are 1.215 and 1.114, indicating that the number of green invention patent applications is higher than the number of green utility model applications. Other control variables are within reasonable ranges.

Table 1. Descriptive Statistics of Main Variables.

	N	Mean	SD	p25	Medium	Min	Max
Total	12,150	2.403	7.032	0.000	0.000	0.000	47.000
Inva	12,150	1.215	3.777	0.000	0.000	0.000	25.300
Uma	12,150	1.114	3.207	0.000	0.000	0.000	20.625
Policy	8,095	0.542	0.498	0.000	1.000	0.000	1.000
Gcres_A	11,757	0.049	0.215	0.000	0.000	0.000	1.000
Gcres_B	12,150	0.345	0.475	0.000	0.000	0.000	1.000
did_A	8,095	0.030	0.169	0.000	0.000	0.000	1.000
did_B	11,757	0.193	0.395	0.000	0.000	0.000	1.000
Inst	12,150	0.552	0.205	0.411	0.557	0.036	0.935
Dual	12,150	0.153	0.360	0.000	0.000	0.000	1.000
Ind	12,150	0.371	0.064	0.333	0.357	0.250	0.563
Mtb	12,150	0.563	0.253	0.362	0.544	0.102	1.126
Cash	12,150	0.555	0.740	0.167	0.312	0.022	4.322
Debt	12,150	0.502	0.192	0.361	0.512	0.075	0.869
Ppe	12,150	0.259	0.186	0.110	0.223	0.002	0.736
Roa	12,150	0.039	0.054	0.012	0.033	-0.158	0.200
Employee	12,150	5.792	9.493	1.059	2.502	0.046	54.599
Tq	12,150	2.031	1.222	1.238	1.626	0.883	7.110

3. Results

3.1. Parallel Trend Test

This paper uses the event study method to test whether the sample data meets the parallel trend assumption. Specifically, the variable $\mathrm{did_k}$ in Model (1) are replaced with the interaction terms $\mathrm{D_{ks}}$, which represents the interaction between the time dummy variable S, constructed with 2016 as the base year, and $\mathrm{Gcres_k}$.The regression equation is as follows:

$$P_{it+1} = \alpha_0 + \alpha_i + \alpha_t + \sum_{s=-4}^{4} \beta_{ks} * D_{ks} + \gamma\chi_{it} + \varepsilon_{it} \quad (2)$$

The test results are shown in Figure 3. The left panel shows results for Group A (HPI), while the right panel shows results for Group B (LPI). Before policy enactment, the estimated coefficients in the left panel fluctuate around 0, with 95% confidence intervals mostly including 0, indicating no significant deviation from 0. After policy enactment, the coefficients are significantly positive, satisfying the parallel trend test. Similarly, the right panel shows that the coefficients fluctuate within a small range around 0 before the policy enactment, indicating no significant effect. After the policy enactment, the coefficients become significantly positive, also satisfying the parallel trend test.

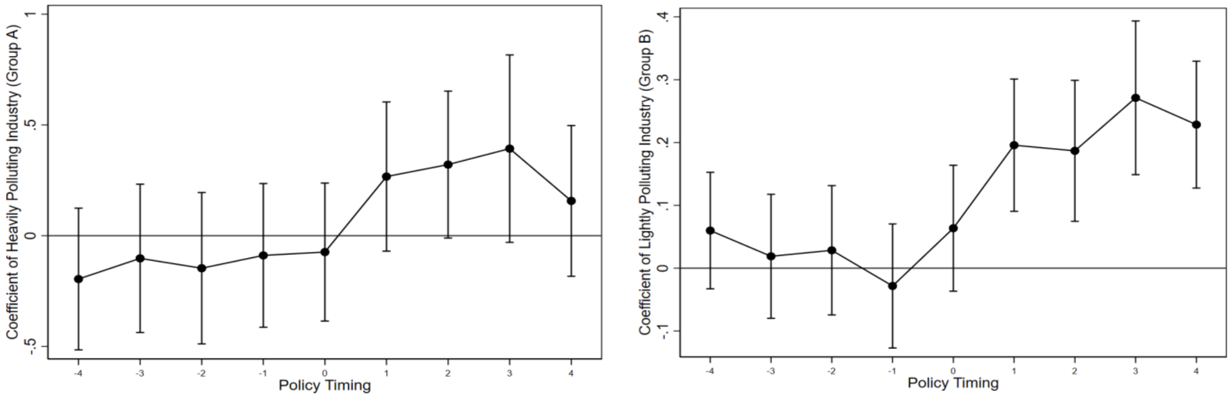

Figure 3. Parallel Trend Test for Group A (Left) and Group B (Right).

3.2. Benchmark Regression Results

The results, as detailed in Table 2, demonstrate that GC has led to an increase in GI for Group A, predominantly in terms of quantity rather than quality. In column (1), the coefficient for did_A is 0.335, significant at the 1% level, indicating a 33.5% increase in green patent applications following the implementation of the "Guiding Opinions." This increase surpasses the 21% reported by Wang Xin's [4]. Columns (2) and (3) reveal that the rise in green patent applications (LnTotal) is primarily driven by green utility model patents (LnUma), with the impact on green invention patents (LnInva) being insignificant, indicating a lack of sufficient incentives for quality improvement.

Table 2. Benchmark Regression Results (Omit some non-significant control variables).

	(1) LnTotal_A	(2) LnInva_A	(3) LnUma_A	(4) LnTotal_B	(5) LnInva_B	(6) LnUma_B
policy	0.340*** (0.036)	0.247*** (0.029)	0.209*** (0.030)	0.323*** (0.032)	0.236*** (0.025)	0.193*** (0.027)
did_K	0.335*** (0.093)	0.117 (0.077)	0.344*** (0.074)	0.163*** (0.037)	0.065** (0.031)	0.159*** (0.030)
Gcres_K	-0.080 (0.253)	-0.028 (0.130)	-0.119 (0.234)	0.062 (0.052)	0.093** (0.041)	0.006 (0.042)
Capital	0.003*** (0.001)	0.002*** (0.001)	0.002*** (0.001)	0.003*** (0.001)	0.002*** (0.001)	0.002*** (0.001)
Roa	0.429** (0.203)	0.252 (0.165)	0.365** (0.165)	0.469*** (0.176)	0.194 (0.139)	0.428*** (0.141)
Employee	0.014*** (0.004)	0.015*** (0.004)	0.010*** (0.002)	0.018*** (0.004)	0.017*** (0.003)	0.012*** (0.003)
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.082 (0.103)	-0.029 (0.085)	0.037 (0.083)	0.034 (0.094)	-0.040 (0.075)	-0.006 (0.077)
N	7813	7813	7813	11330	11330	11330

Note: Standard errors are in parentheses. * p<0.1, ** p<0.05, *** p<0.01. Same applies below.
For Group B, the findings indicate several important trends. First, compared to the "Guidelines" policy period, the increased focus on GCP within Group B has led to a significant enhancement in GI. Additionally, the tendency to prioritize quantity over quality in innovation is less pronounced when compared to Group A, reflecting a more balanced approach. Moreover, Group B has considerable room for future growth in GC and GI integration.

The results in column (4) show that the coefficient for did_B is 0.163, significant at the 99% confidence level, indicating a 16% increase in green patent applications compared to ordinary industries. Column (5) shows a 6.5% increase in LnInva, suggesting an improvement in innovation quality, though modest. Furthermore the coefficient for Gcres_B in column (5) is 0.093 at the 95% confidence level, indicating that LPI tend to have higher-quality GI compared to ordinary industries .

Overall, the did_B coefficients in columns (4), (5), and (6) (0.163, 0.065, 0.159) are statistically significant, they are smaller than the corresponding did_A coefficients (0.335, 0.344). This suggests that the current incentive mechanisms for GI in LPI may require further refinement. As GC stabilizes within HPI, their innovation output is expected to reach a stable state. However, to achieve carbon neutrality and peak emissions, continued and enhanced green innovation will be essential. The current impact of GCP on LPI is less than half that observed on HPI, highlighting the substantial potential for growth in this area.

3.3. Robustness Check (Considering the long-term nature of GI)

Given that innovation typically requires a longer cycle[11], this study conducts robustness checks using data lagged by two and three years. The results in Table 3 show that the coefficients of did_B are significant across all six models, indicating that GCP have a long-term positive effect on the quality and quantity of GI in LPI.

Further analysis reveals that the coefficients of did_B in year (t+2) are 0.189, 0.08, and 0.196, which are significantly higher than the corresponding coefficients in year (t+1) (i.e., the benchmark regression) and year (t+3). This result suggests that the impact of GCP on GI in LPI follows a gradually increasing trajectory, peaking in the third year, and then stabilizing over time.

Table 3. Robustness Check (Omit control variables and some non-significant variables).

	(t+2) year			(t+3) year		
	LnTotal_B	LnInva_B	LnUma_B	LnTotal_B	LnInva_B	LnUma_B
policy	0.326***	0.246***	0.192***	0.283***	0.217***	0.161***
	(0.031)	(0.025)	(0.026)	(0.033)	(0.026)	(0.027)
did_B	0.189***	0.080***	0.196***	0.165***	0.064**	0.181***
	(0.037)	(0.031)	(0.031)	(0.040)	(0.032)	(0.033)
Control	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.160	0.048	0.091	0.113	0.091	0.004
	(0.103)	(0.084)	(0.078)	(0.112)	(0.091)	(0.085)
N	9209	9209	9209	8167	8167	8167

4. Conclusions

This paper examines the impact of GCP on GI in low-pollution enterprises, based on the policy of the "Guiding Opinions on Building a Green Financial System." DID test results show that after the implementation of the "Guiding Opinions," attention to GC in LPI has increased, leading to significant improvements in GI. Further comparison with the results for HPI indicates that the issue of "quantity over quality" in GCP is alleviated in LPI, which have greater potential for GI and GC.

Robustness checks using lagged data reveal that the positive effect of GCP on GI has a significant delay, peaking in the third year after policy implementation. The study provides two policy insights:

(1) Enhancing the GC Policy System: The potential and delayed effects in LPI suggest that the top-level design of GCP should continue to increase the total GC supply to these industries to ensure sustained policy effectiveness.

(2) Guiding Substantive Innovation: The current issue of "quantity over quality" in GC requires specialized and differentiated credit products. By refining the identification and evaluation of different categories of green technological innovations, the policies can more accurately identify enterprises with true GI capabilities and guide them to build core competitiveness.

References

[1] Han H. W., Gan Y. T. Can investor attention promote the improvement of corporate green innovation performance?—the mediating effect of financing constraints and the moderating role of environmental regulation [J]. Science & Technology Progress and Policy, 2023, 40(08): 89-98.

[2] Ma J., Guan Y. X. The impact of environmental regulation on corporate green innovation—a study based on listed A-share companies in China's heavily polluting industries [J]. Innovation and Technology, 2022, 22(05): 71-82.

[3] Xia L., Gao S., Wei J., Ding Q. Government subsidy and corporate green innovation - Does board governance play a role?[J]. Energy Policy, 2022, 161: 112720.

[4] Wang X., Wang Y. Research on the enhancement of green innovation by green credit policy [J]. Management World, 2021, 37(06): 173-188.

[5] Yu L. C., Zhang W. G., Bi Q. The reverse pressure effect of environmental tax on corporate green transformation [J]. China Population, Resources and Environment, 2019, 29(07): 112-120.

[6] Shu L. M., Liao J. H., Xie Z. Green credit policy and corporate green innovation—Empirical evidence based on the perspective of green industry [J]. Journal of Financial Economics Research, 2023, 38(02): 144-160.

[7] Lu J., Yan Y., Wang T. X. A study on the micro effects of green credit policy—from the perspective of technological innovation and resource reallocation [J]. China Industrial Economics, 2021, (01): 174-192.

[8] Cai H. J., Wu Y. F., Zhou C. The impact of government environmental regulation intensity on corporate carbon information disclosure—based on the perspective of board independence [J]. Finance and Accounting Monthly, 2019, (24): 83-89.

[9] Lei Z. H., Guo A. J. Can green credit policy affect corporate total factor productivity?—Empirical evidence from listed A-share companies [J]. Journal of China University of Geosciences (Social Sciences Edition), 2023, 23(06): 100-113.

[10] Li W. J., Zheng M. N. Substantial innovation or strategic innovation?—the impact of macro industry policy on micro enterprise innovation [J]. Economic Research Journal, 2016, 51(04): 60-73.

[11] Yang Y., Zhang Y. The impact of the green credit policy on the short-term and long-term debt financing of heavily polluting enterprises: Based on PSM-DID method[R]. 2022, 19(18): 11287.