# Can Green Credit Policies Promote Coordinated Carbon Pollution Reduction? Evidence from a Difference-in-Differences Model

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## Abstract

Green credit policy is an important tool to promote the green and clean development of the industrial sector. the transformation effect of the industrial sector directly affects the global climate governance process. To explore how green financial policies will impact coordinated carbon pollution emission reduction, this study uses the double difference model (DID) to evaluate the impact of green financial policies on coordinated carbon pollution emission reduction. Constructing an Empirical Analysis of Provincial Panel Data in China from 2008 to 2021. Results show that the green credit policy significantly inhibited the synergistic emission of carbon pollution, with a coefficient of -0.0278, and had a synergistic and significant effect on the total pollutant emissions. The mechanism test shows that the policy drives emission reduction through the path of technological innovation; however, the mechanism of industrial structure adjustment and energy efficiency has not reached a significant level. Furthermore, the policy effect is more significant in areas with high economic levels, areas with low proportions of secondary industry, and areas with high environmental regulation, revealing the heterogeneity of regional economic structure, industrial dependence, and environmental supervision on policy transmission. Based on this, we proposed some recommendations: to strengthen the regional adaptability of green financial instruments, focus on technological innovation incentives, and break heterogeneous bottlenecks through differentiated policy design to improve the efficiency of collaborative governance of carbon pollution and help promote the synergy of global climate goals and sustainable development agendas.

# Full Text

## Can Green Credit Policies Promote Coordinated Emission Reduction of Carbon Pollution? Evidence from a Difference-in-Differences Model

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### Abstract

Green credit policy represents a crucial instrument for advancing green and clean development in the industrial sector, whose transformation effects directly influence global climate governance processes. To investigate how green financial policies impact coordinated carbon pollution emission reduction, this study employs a difference-in-differences (DID) model to evaluate the effects of green financial policies on coordinated carbon pollution emission reduction using provincial panel data from China spanning 2008 to 2021.

Our results demonstrate that green credit policy significantly inhibits the synergistic emission of carbon pollution, with a coefficient of -0.0278, and exhibits a synergistic and significant effect on total pollutant emissions. Mechanism testing reveals that the policy drives emission reduction primarily through the pathway of technological innovation; however, the mechanisms of industrial structure adjustment and energy efficiency improvement have not reached statistically significant levels. Furthermore, the policy effect proves more pronounced in regions with high economic development levels, low proportions of secondary industry, and strong environmental regulation, revealing how regional economic structure, industrial dependence, and environmental supervision create heterogeneity in policy transmission. Based on these findings, we propose several recommendations: strengthen the regional adaptability of green financial instruments, focus on technological innovation incentives, and break through heterogeneous bottlenecks through differentiated policy design to improve the efficiency of collaborative carbon pollution governance and advance the synergy between global climate goals and sustainable development agendas.

**Keywords:** Green credit; Carbon-pollution synergy; Difference-in-differences model; Panel data

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## 1 Introduction

Under the dual pressures of global climate change and ecological crisis, traditional high-pollution and high-energy-consuming industries face unprecedented transformation challenges. As the source of 37% of global carbon emissions and 52% of pollutant emissions, the industrial sector' s extensive development model has reached the critical limits of environmental carrying capacity. Notably, carbon emissions and pollutant emissions often exhibit homologous characteristics —that is, they share common sources and driving factors in production processes. This homologous characteristic indicates that policy evaluations focusing solely on either carbon emissions or pollutant emissions likely overlook the synergistic interplay between them, resulting in incomplete assessments of environmental governance efficacy and a fragmented understanding of policy impacts. However, existing policy tools have paid insufficient attention to this critical feature in their design and implementation, leading to carbon emission effects becoming the primary basis for policy judgment while ignoring the potential value of collaborative carbon-pollution governance.

As both a groundbreaking financial innovation and precursor to formalized eco-financing systems, green credit policy established early standardization benchmarks in sustainable banking, aiming to solve the dilemma of "externalization of environmental governance costs" by guiding capital toward clean technology research and development and green industry upgrading. With its relatively mature regulatory frameworks and broad applicability across industries, green credit has established itself as a foundational pillar of sustainable finance systems since its inception in the early 2000s. However, current research predominantly focuses on the single emission reduction or economic effects of green financial policies, lacking systematic analysis of the collaborative governance mechanism of carbon pollution—despite green credit' s unique position as a policy instrument integrating both mandatory environmental standards and market-driven capital allocation. This theoretical gap not only limits comprehensive policy effect assessment but may also hinder the accurate application of pioneering green financial instruments like credit mechanisms in environmental governance. Therefore, in-depth investigation of how these established yet evolving green financial policies drive coordinated carbon and pollution emission reduction can reveal multi-faceted policy impacts while leveraging credit instruments' dual advantages of regulatory enforceability and market penetration, offering more scientific and actionable strategies for global climate governance.

To address this problem, we systematically analyze the impact of green credit policies on coordinated emission reduction of greenhouse gases and pollutants based on panel data from 30 provincial administrative divisions in China from 2008 to 2021. By introducing the theoretical framework of "collaborative control of carbon pollution," we further examine three pathways: industrial structure upgrading, technological innovation, and energy efficiency improvement. Investigating this synergy is crucial because climate change and environmental pollution represent interrelated challenges, and effective governance requires integrated strategies to avoid fragmented policies that address one issue while ignoring the other, thereby unlocking co-benefits for public health, ecological protection, and climate resilience. This research also aligns organically with the ongoing temperature control goals of the Paris Agreement and the United Nations Sustainable Development Goals (SDGs), ensuring that climate action and pollution mitigation reinforce rather than undermine each other. The marginal contribution of our study lies in its explicit focus on carbon-pollution synergies, aiming to provide empirical evidence for policymakers to optimize green financial instruments.

## 2 Literature Review

### 2.1 Multi-dimensional Implementation Effects of Green Credit Policy

Most research on green credit has concentrated on its economic and environmental effects. The existing literature has conducted multi-dimensional discussions on these dimensions. Regarding economic effects, Wang et al. (2021) found through a difference-in-differences model that green credit significantly improved financing availability for clean technology companies through differentiated interest rate policies, while creating an inhibitory effect of approximately 12.7% on fixed asset investment in highly polluting industries. This structural adjustment brought about a 3.2% improvement in overall economic efficiency. At the environmental effects level, Zhang and Chen (2022) reported that compared with the control group, carbon emission intensity per unit GDP in regions implementing green credit policies decreased by 4.8% annually, with the mechanism reflected in promoting clean energy structure and increased technological innovation investment. The effect of pollutant emission reduction exhibits industry heterogeneity: Liu et al. (2023) conducted research based on panel data of industrial enterprises and found that green credit reduced SO emissions in key controlled industries by 14.6%, while COD emissions in the chemical industry decreased by only 5.2%, reflecting differences in industry adaptability during policy implementation.

However, existing studies predominantly focus on analyzing the emission reduction or economic effects of green financial policies, with insufficient theoretical explanation for the collaborative governance mechanism of carbon pollution under policy influence. In fact, carbon emissions and pollutant emissions often exhibit homologous characteristics (Chen, 2023; Lee and Wang, 2022; Liu and Dong, 2019; Wang et al., 2020; Zhang et al., 2021). This synergistic effect of environmental governance under dual constraints can not only overcome the high-cost dilemma of traditional end-of-pipe treatment but also achieve environmental quality improvement through the endogenous drive of green technology. Therefore, in-depth analysis of the mechanism and transmission path of green financial policies on coordinated carbon pollution emission reduction is urgently needed.

### 2.2 Research Status of Carbon-Pollution Synergy Effects and Policy Correlation Deficiencies

Although the concept of carbon-pollution synergy has attracted academic attention, existing research predominantly focuses on the synergistic effects of technology paths. For example, Yang et al. (2020) constructed a coupling model and concluded that ultra-low emission transformation of coal-fired power plants can simultaneously achieve a 12% reduction in CO  emissions and a 45% reduction in PM2.5. However, this technology-oriented research generally lacks perspective on policy intervention. Notably, only 6.3% of collaborative studies on carbon pollution in the existing literature involve analysis of policy factors, with most limited to impact assessments of environmental regulatory tools (Zhang et al., 2022). Particularly, as a market-oriented environmental governance tool, the synergistic effect of green credit policy on carbon pollution through the fund allocation mechanism has not been fully explained (Zhang et al., 2021; Wang and Liu, 2020). This "black box" state of the policy mechanism directly leads to two key unresolved issues: first, whether policies such as green credit produce systemic synergistic effects through industrial structure adjustment (Zhang et al., 2021); second, whether there are nonlinear characteristics in the impact of different policy tool combinations on the carbon pollution synergy coefficient (Doda et al., 2016).

### 2.3 Research Gaps and Marginal Contributions

Existing research has three significant limitations. First, policy effect assessment mostly uses single environmental indicators, lacking systematic analysis of coordinated management of carbon emissions and pollutants. Second, few empirical studies have systematically examined the dual impact mechanisms of climate-aligned financial policies on coordinated carbon and pollutant reduction, with existing studies mostly based on linear transmission assumptions and failing to fully examine how green financial policies impact carbon-pollution synergy. Finally, existing models fail to effectively integrate financial market signals with real sector transformation dynamics.

Based on these gaps, our potential contributions are as follows. First, we systematically examine the impact of green financial policies on collaborative governance of carbon pollution from the perspective of homologous characteristics for the first time. Second, we analyze the role of green credit policy in technological innovation, industrial structure, and energy efficiency mechanisms. Third, we reveal the differential impacts of green financial policies on carbon-pollution synergy across different regions through heterogeneity analysis.

# 3 Methodology

## 3.1 Policy Background

As of 2025, China has implemented various green credit policies. In 2011, 2012, and 2016, China successively issued a series of policies including the "Carbon Emissions Trading Pilot," "Green Credit Guidelines," and "Building a Green Financial System." In 2017, seven ministries and commissions jointly issued the "Green Credit Reform and Innovation Pilot Zone"policy in some provinces across eastern, central, and western regions. Based on this policy background, this paper primarily studies the impact of green credit policy on carbon pollution synergy in provincial administrative divisions. Due to missing and undisclosed data in most regions, this study selected 30 provincial administrative divisions (excluding Tibet, Hong Kong, Macao, and Taiwan) from 2008 to 2021 for analysis. According to the policy implementation, 10 green credit pilot provincial units serve as the treatment group, with other provincial units as the control group, yielding 420 observation units across 20 provincial administrative divisions from 2008 to 2021.

## 3.2 Model Specification

The difference-in-differences (DID) model is a quasi-experimental research design using observational data. The basic approach divides the data into two groups: one group covered by the pilot policy serves as the treatment group, while the other group not subject to intervention serves as the control group (Angrist and Pischke, 2008). As of 2025, there are 7 provincial administrative units in the "carbon emission rights"pilot and 5 pilot zones for "green credit,"with 2 provincial administrative units participating in both policies simultaneously.

Based on the fact that the "green credit policy" was first proposed in 2011, we designate provincial administrative units where the policy was implemented as the treatment group and remaining samples as the control group. Taking 2011 as the policy intervention point, the econometric model is established as follows:

$$Y_{it} = \beta_0 + \beta_1 D_i + \beta_2 T_t + \beta_3 (D_i \times T_t) + \lambda C_{it} + \mu_i + \gamma_t + \varepsilon_{it}$$

where $Y_{it}$ is the outcome variable, $D_i$ is the policy grouping dummy variable, $T_t$ is the policy time dummy variable, $D_i \times T_t$ is the interaction term, $C_{it}$ represents control variables, $\beta$ and $\lambda$ are coefficients, and $\varepsilon_{it}$ is the random error term. $\mu_i$ and $\gamma_t$ are individual fixed effects and time fixed effects, respectively, which can be controlled by adding individual dummy variables and time dummy variables in regression.

## 3.3 Variable Measurement

**3.3.1 Dependent Variable** The dependent variable is the carbon-pollution synergistic coupling index, comprising three dimensions: total apparent carbon dioxide emissions (C), total pollutant emissions (P), and the carbon-pollution synergistic coupling index (CP). C reflects China' s overall carbon emission levels and trends, P reflects total air pollutant emissions (primarily measured by SO ), and CP reflects the synergistic effect of carbon pollution. Considering the consistency of statistical units for C and P and the overall right-skewed distribution, the data are normalized and coupled to obtain the CP term.

**3.3.2 Independent Variables** The core explanatory variable is the green credit indicator. Based on the "carbon emission rights" and "green credit policies" mentioned above, we set the provincial administrative division unit index ($D_i$) to 1 for green credit pilot regions (treatment group = 1, control group = 0). Since the policy implementation year is 2011, the policy implementation year indicator ($T_t$) is set to 0 before 2011 (excluding 2011) and 1 after 2011. The core explanatory variable (Policy) is obtained by multiplying the provincial administrative division unit indicator ($D_i$) of the green credit pilot project with the policy implementation year indicator ($T_t$).

**3.3.3 Control Variables** Referring to previous literature, we set control variables as shown in Table 1 : (1) Annual power generation (PG) of provincial units, which serves as an important "bridge" indicator reflecting regional carbon pollution emissions and economic development; (2) Consumer price index of public transport fees (TP), which reflects cost changes in public transportation services that may directly or indirectly affect carbon emissions and environmental pollution levels; (3) Gross domestic product (GDP), which measures regional economic development levels and reflects industrial, manufacturing, and handicraft sector performance; and (4) GDP growth rate (RG), which similarly measures regional economic development while considering time effects to reflect short-term regional development. Variables (1), (2), and (3) are normalized in the analysis due to statistical unit consistency issues and positive values.

**Table 1 Data Description**

| Description | Power generation | Consumer Price Index of Public Transport Fees | Regional GDP | Regional GDP growth rate | Total apparent CO emissions | Pollutant emissions | Carbon-pollution coupling index | Share of secondary industry | Number of granted patent applications | Energy consumption per unit of GDP |
|---|---|---|---|---|---|---|---|---|---|---|
| VarName | PG | TP | GDP | GR | C | P | CP | AS | ZP | EB |

### 3.4 Data Sources

All data in this study are from the China Statistical Yearbook, China Green Credit Policy Text Database (CNRDS), the International Institute of Green Credit (IIGF) of the Central University of Finance and Economics, and the China Carbon Accounting Database (CEADs) (Xu et al., 2024; Guan et al., 2021; Shan et al., 2020; Shan et al., 2018; Shan et al., 2016).

## 4 Empirical Results

### 4.1 Baseline Regressions

Columns (1), (2), and (3) in Table 2 show the impact of green credit policy on China' s total apparent carbon dioxide emissions, total pollutant emissions, and synergistic coupling index without control variables. The results show that green credit policy significantly affects item C at $p < 0.01$ with a negative coefficient of -0.000504. While green credit policy has no significant impact on carbon pollution initially, further analysis reveals that the synergistic effect of green credit policy on carbon pollution is negative and significant at -0.036 when $p < 0.01$. These findings indicate that green financial policies can inhibit total apparent carbon dioxide emissions, and although the effect on total pollutant emissions is not significant, the implementation of green financial policies can substantially inhibit the synergistic effect of carbon pollution emissions when the carbon-pollution synergistic coupling index is introduced.

Columns (4), (5), and (6) of the table further introduce control variables PG, TP, GDP, and GR. The data show that after introducing these variables, the synergistic effect of green credit policy on carbon pollution and carbon pollution remains significant at $p < 0.01$ with negative relationships, while the effect on carbon pollution alone remains insignificant. The coefficients of green credit policy on carbon pollution and carbon pollution synergy become -0.000301 and -0.0278, respectively. Results analysis indicates that green financial policies can inhibit synergistic indicators of total apparent carbon dioxide emissions and carbon pollution emissions, but increases in power generation, public transportation investment, regional GDP, regional GDP growth rate, and per capita GDP growth rate may delay the inhibitory effect of green financial policies.

**Table 2 Baseline Regression**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Green Credit Policy | -0.000504*** | 0.00164*** | -0.0360*** | -0.000301* | 0.00298*** | -0.0278** |
| | (0.000169) | (0.000122) | (0.0122) | (0.000159) | (0.000693) | (0.0123) |
| Constant | 0.00368*** | 0.837*** | 0.589*** | 0.699** | 0.909*** | -14.16*** |
| | (0.000144) | (0.00886) | (0.0723) | (0.277) | (0.0479) | (3.797) |
| Observations | | | | | | |

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| R-squared | | | | | | |

*Standard errors in parentheses.* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.*

#### 4.2 Parallel Trend Test

The effectiveness of DID depends on parallel trends in outcome variables between the treatment and control groups before intervention (Angrist & Pischke, 2008). The parallel trend test is a key step in the DID model to verify whether treatment and control groups exhibit the same trend before policy implementation (Lechner, 2011). If intervention and control groups show parallel patterns prior to policy implementation, we can more confidently attribute post-policy differences to the policy itself, ensuring accurate causal inference and improving research credibility (Lechner et al., 2011; Beck et al., 2010; Angrist et al., 2009).

The core premise of our DID model is that before the green credit policy took effect, the carbon-pollution synergistic coupling index (CP) showed no statistically significant difference between the experimental and control groups, but exhibited significant differentiation after policy implementation. Using regression results from Table 2, Figure 1 [Figure 1: see original paper] plots time on the horizontal axis and regression coefficients on the vertical axis. The effect sizes at -2 and -1 before policy implementation are not significant, indicating no significant difference in trends between treatment and control groups before the policy, consistent with the parallel trend hypothesis. From time point 1 onward, the effect size continues to rise ($1 \rightarrow 10$), showing significant and sustainable policy effects.

**Fig 1 Parallel trend test**

#### 4.3 Placebo Tests

A placebo test examines model robustness by simulating "false treatment" and serves as an important tool for identifying causal effects (Angrist & Pischke, 2008). By eliminating interference from other potential factors, research conclusions become more reliable. The main principle involves constructing pseudo-policy or pseudo-treatment to test whether real policy effects are reliable (Athey et al., 2017; Bertrand et al., 2004; Imbens et al., 2015). To eliminate interference factors, this study randomly selects samples, randomly generates policy implementation times, constructs new green credit policy pilot cities and implementation times, runs 300 simulations, and presents placebo test results in Figure 2 [Figure 2: see original paper].

According to Figure 2, coefficients of green financial policies after randomization are normally distributed and concentrated around 0, with most p-values above 0.1. The random coefficient is located to the right of -0.026, indicating that after randomization, policy effects are significantly weakened in both significance and effect strength, confirming that our main findings are robust.

**Fig 2 Placebo test**

# 5 Mechanism Analysis and Heterogeneity

## 5.1 Mechanism Analysis

**5.1.1 Mechanism Model Establishment** When analyzing mechanism effects of industrial structure and energy efficiency, we observe that green credit policy not only restricts loans to high-carbon industries but also supports development of energy-saving and environmental protection industries such as new energy, thereby reducing the proportion of high-pollution industries in the secondary sector. Additionally, green credit policy supports research and development of new energy technologies, increases the number of technology patents, and promotes low-carbon energy structure transformation. The policy also provides low-interest loans for upgrading industrial energy-saving equipment, encouraging enterprises to adopt high-efficiency motors or waste heat recovery technology to reduce energy consumption per unit output. Therefore, based on previous scholars' experience, this study examines the influence mechanisms of industrial structure, technological innovation, and energy efficiency on the carbon-pollution economy.

Our focus is on green credit' s impact on the carbon-pollution economy under "carbon emission rights" and "green credit pilot" policies, requiring further verification of our intermediary variable hypotheses. To examine these mechanisms, we construct the following model:

$$G_{it} = \alpha_0 + \alpha_1(D_i \times T_t) + \alpha_2 C_{it} + \mu_i + \gamma_t + \varepsilon_{it}$$

where $G_{it}$ represents mechanism outcome variables, and other variables maintain consistent definitions. In this study, mechanism variables include: industrial structure adjustment mechanism, technological innovation mechanism, and energy efficiency mechanism, measured by the proportion of secondary industry (AS), number of granted patent applications (ZP), and energy consumption per unit GDP (EB).

**5.1.2 Mechanism Results** Mechanism effect test results for industrial structure and energy efficiency are shown in Table 3 . Column (1) shows that the synergistic effect of green credit policy on carbon pollution is -0.278, passing the 5% significance level, indicating that green financial policies improve carbon-pollution emissions. In Column (2), the coefficient of green credit policy on AS is -3.0173, indicating that green credit policy plays a negative role in industrial structure adjustment. In Column (3), the coefficient of green credit policy on EB is 2.6263, indicating a positive mechanism effect on energy efficiency. However, p-value analysis shows that green credit policy is not significant for

AS and EB, indicating that industrial structure and energy efficiency show no significant changes, requiring further mechanism analysis.

**Table 3 Mechanism effects of overall industrial structure and energy efficiency**

| | (1) | (2) | (3) |
|---|---|---|---|
| Green Credit Policy | -0.0278** | -3.0173 | 2.6263 |
| | (0.0123) | | |
| Constant | -14.16*** | 0.171*** | 0.0269** |
| | (3.797) | (0.0578) | (0.0115) |
| Observations | | | |
| R-squared | 0.909 | | |

According to Table 4 , Column (2) shows that the coefficient of green credit policy on ZP is 0.000810 with a positive sign, indicating that green financial policies have a positive mechanism effect on technological innovation level adjustment. This demonstrates that green financial policies primarily impact carbon-pollution economies through technological innovation mechanisms. Environmental regulations may stimulate innovation and enhance corporate competitiveness rather than merely increasing costs (Porter and Van Der Linde, 1995). In the context of green credit policy, such policies may promote development of low-carbon and high-efficiency technologies by setting environmental standards and market incentives. As companies face higher environmental standards, they meet these requirements through technological innovation, thereby curbing carbon emissions while enhancing resource efficiency. The cost hypothesis further promotes technological innovation because green credit policies are often accompanied by regulatory and compliance requirements, and companies must make additional environmental protection investments. If compliance costs are too high, businesses may be more inclined to seek technological innovations to reduce these costs.

Taken together, technological innovation plays a vital role in green credit policies' impact on the carbon-pollution economy. Through Porter' s hypothesis, green credit policies encourage enterprises to develop new environmentally friendly technologies by creating innovation opportunities, thereby improving industry greening levels. Simultaneously, compliance cost pressures prompt enterprises to innovate, particularly regarding emission reduction and resource utilization efficiency, to cope with increasingly stringent environmental regulations and market demands.

**Table 4 Mechanism Effect of Technological Innovation**

| | (1) | (2) |
|---|---|---|
| Green Credit Policy | -0.0278** | 0.000810** |

| | (1) | (2) |
|---|---|---|
| | (0.0123) | (0.000325) |
| Constant | -14.16*** | 2.629*** |
| | (3.797) | (0.100) |
| Observations | | |
| R-squared | 0.909 | |

## 5.2 Heterogeneity Analysis

**5.2.1 Economic Development Heterogeneity** Differences in regional economic development levels often lead to significant heterogeneous policy effects. According to Stiglitz (2015), the impact of green financial policies on the real economy is affected by regional financial market maturity, corporate financing constraints, and government governance capabilities. Regions with high economic levels usually have more complete green financial infrastructure, allowing green financial policies to more effectively transmit to emission reduction behaviors through market mechanisms in areas with high financial deepening. This paper explores policy heterogeneity arising from these economic differences. Following Hao & Naiman (2007), we divide regional economic heterogeneity by the 50th percentile, which avoids extreme value interference (statistical robustness) while balancing sample size to improve test power.

For regional economic differences, this paper uses per capita GDP measurements, classifying the top 50% regions as high-economic regions and the bottom 50% as low-economic regions. Economic development heterogeneity results are reported in Table 5 . In high-economic development areas, the pre-term coefficient of green financial policies on carbon pollution synergy is -0.039 at the 10% significance level, while in low-development areas, the synergistic effect is not significant. This indicates that green financial policies have more obvious effects in high-economic development regions, possibly because low-development regions lack complete green financial infrastructure and cannot quickly transmit emission reduction behaviors, resulting in insignificant policy effects. Therefore, it is necessary to implement green credit policies competitively, with forward-looking deployment for low-income areas.

**Table 5 Analysis results of heterogeneity of economic development**

| | High economic zone | Low economic zone |
|---|---|---|
| Green Credit Policy | -0.039* | 0.021 |
| | (0.015) | (0.021) |
| Constant | 7.431 | 8.540 |
| | (17.790) | (95.356) |
| R-squared | 0.863*** | 0.949*** |
| | (0.047) | (0.226) |

**5.2.2 Industrial Structure Heterogeneity** According to Copeland and Taylor (2004), the secondary industry is the main source of carbon emissions, and its proportion directly affects regional pollution intensity. Based on this theory, we explore heterogeneity resulting from differences in secondary industry development levels. Consistent with the economic development heterogeneity analysis, we use the proportion of regional secondary industry to measure this characteristic and divide heterogeneity by the 50th percentile. The top 50% regions by secondary industry proportion are classified as high secondary industry areas, while those below 50% are low secondary industry areas.

According to results in Table 6 , the synergistic effect of green financial policies on carbon pollution is not significant in high secondary industry proportion areas, while in low proportion areas, the effect is significant at the 5% level with a coefficient of -0.055, indicating that green financial policies are more effective in regions with low secondary industry proportions. This suggests that regional economies highly dependent on industry, with large numbers of industrial enterprises bound to traditional high-carbon industries, create a "resource curse" effect. The low-carbon transformation promoted by green financial policies requires substantial sunk costs, which may impact local economic stability in the short term. Therefore, green financial policies are often insignificant in high secondary industry proportion areas. We recommend both extending policy influence advantages in low secondary industry regions and formulating active incentive policies to promote enterprise transformation into green enterprises.

**Table 6 Results of heterogeneity analysis of industrial structure**

| | High secondary industry | Low secondary industry |
|---|---|---|
| Green Credit Policy | 0.015 | -0.055** |
| | (9.744) | (0.019) |
| Constant | -287.149*** | -39.712*** |
| | (83.101) | (10.667) |
| R-squared | 1.528*** | 0.865*** |
| | (0.197) | (0.058) |

**5.2.3 Environmental Regulation Heterogeneity** According to Porter and Van Der Linde' s (1995) "Porter Hypothesis," strict environmental regulations can offset compliance costs and enhance long-term competitiveness by forcing enterprise innovation. Copeland and Taylor' s (2004) "pollution shelter hypothesis" shows that differences in environmental regulation lead to transfer of highly polluting industries to loosely regulated areas, weakening overall emission reduction effects. Through analysis of these theories, differences in environmental regulation also produce significant heterogeneous policy effects. This paper uses the proportion of environmental investment to total regional GDP to measure environmental regulation intensity and divides heterogeneity by the 50th percentile, with top 50% regions classified as high environmental regulation intensity areas and those below 50% as low intensity areas.

According to results in Table 7 , in high environmental regulation areas, the coefficient of green credit policy on carbon pollution synergy is -0.047 at the 10% significance level. Regions with underdeveloped environmental oversight demonstrate limited interactive outcomes between green credit mechanisms and carbon mitigation. The data show that green credit policy effects are more significant in areas with high environmental regulation but not in areas with low regulation. This indicates that strong environmental regulations and substantial external pressure on enterprise green development may be more conducive to carbon trading markets promoting carbon-pollution synergy. Our results are consistent with Borghesi et al. (2015), who found that for every unit increase in the environmental regulation index, the marginal effect of green bond financing on industrial emission reduction is enhanced by 15%, verifying policy synergy effects and further validating this study' s effectiveness.

**Table 7 Results of environmental regulatory heterogeneity analysis**

| | High environmental regulation | Low environmental regulation |
|---|---|---|
| Green Credit Policy | -0.047* | 0.014 |
| | (0.020) | (0.014) |
| Constant | 40.282** | 5.845 |
| | (14.559) | (16.465) |
| R-squared | 0.839*** | 0.821*** |
| | (0.204) | (0.047) |

## 6 Conclusions and Recommendations

Based on panel data from 30 Chinese provinces from 2008 to 2021, this study systematically evaluates green credit policies' impact on coordinated carbon pollution emission reduction and their transmission mechanisms using a difference-in-differences (DID) model. Through parallel trend tests, placebo tests, and heterogeneity analysis, we verify the robustness of policy effects. Our findings are: (1) Green financial policies have significant inhibitory effects on coordinated carbon pollution emissions. This paper empirically analyzes the significant effect of green credit policy on coordinated carbon pollution emission reduction, verified through a series of robustness tests. (2) Green financial policies primarily affect coordinated carbon pollution emission reduction through technological innovation pathways. The policy significantly increases the number of granted patent applications and promotes enterprises to reduce carbon emission intensity through clean technology research and development. However, the intermediary roles of industrial structure adjustment and energy efficiency improvement are not significant, indicating that policies still need strengthening in promoting transformation of high-carbon industries and application of energy-saving technologies. (3) Green credit policy effects show significant differences across economic development levels, industrial structures, and environmental regulations. The policy has significant effects on coordinated carbon pollution emission reduction in high-economic-level areas but not in low-level areas, possibly due to lack of green financial infrastructure support. Policy effects are more significant in areas with low secondary industry proportions, while the "resource curse" effect in industrially dependent areas inhibits policy transmission. Regional policies with high environmental regulation demonstrate remarkable effects, indicating synergy between strict environmental supervision and green financial policies.

Based on these findings, we propose several policy recommendations:

First, continuously promote the development experience of green policies and strengthen policy experience exchange and learning among regions to accelerate replication and promotion of green credit models. For example, some regions have explored replicable regulatory frameworks and incentives by establishing green credit reform and innovation pilot zones, providing valuable references for other regions.

Second, technological innovation is a key pathway for promoting collaborative carbon pollution governance, and optimizing policy transmission mechanisms can effectively stimulate innovation potential. The government should establish a special clean technology research and development fund focusing on cutting-edge fields such as renewable energy and carbon capture and storage (CCUS). Simultaneously, it should improve the green patent conversion platform, promote industry-university-research cooperation, and enhance technology implementation efficiency. For high-carbon industries (such as steel and cement), implement a two-way "innovation incentive-emission constraint" mechanism: provide tax relief or subsidies for enterprises actively investing in technological upgrading while imposing stricter carbon quota restrictions or fines on enterprises exceeding emissions, creating a "carrot and stick" driving effect. Additionally, strengthen policy supporting measures such as establishing a technology certification system and promoting the catalog of best available technologies (BAT) to help enterprises clarify technology upgrading directions and reduce transformation uncertainty.

Third, strengthen application of green financial instruments to promote precise policy implementation. In high-economic-level areas, promote market-oriented tools such as green bonds and ESG investment to expand policy coverage. In low-economic-level areas, increase financial subsidies and targeted green credit support while improving green financial infrastructure.

Fourth, implement differentiated policies according to local conditions. In areas with low secondary industry proportions, promote green credit pilot experiences and strengthen policy demonstration effects by expanding green credit interest discount scopes, exploring ecological compensation mechanisms, and leveraging demonstration effects. In industrially dependent areas, support industrial transformation compensation mechanisms to reduce sunk cost resistance, establish special transformation funds, and provide employee re-employment training to alleviate short-term pain. Regional coordination is crucial for narrowing policy effect gaps: technologically developed regions can deliver green technologies, talent, and funds to underdeveloped regions through "counterpart support" models, such as establishing cross-regional carbon market alliances and jointly conducting technological research projects. The central government can also balance regional development resources through transfer payments or policy inclination to avoid efficiency losses from "one size fits all" policies.

Finally, deepen synergy between environmental regulation and green credit. In high environmental regulation areas, explore the "carbon trading + green credit" linkage model to enhance marginal emission reduction effects. In loosely regulated areas, gradually improve environmental protection standards to avoid the "pollution shelter" effect weakening overall emission reduction effects.

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*Note: Figure translations are in progress. See original paper for figures.*