

Article

The Green Finance Pilot Policy Suppresses Green Innovation Efficiency: Evidence from Chinese Cities

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Abstract

Green finance is widely promoted as a tool for supporting low-carbon development, but its effects on innovation efficiency remain unclear. This study examines the impact of China's Green Finance Reform and Innovation Pilot Zones (GFRIPZ) on green innovation efficiency at the city level. Using the GFRIPZ policy as a quasi-natural experiment, we employ a difference-in-differences approach to identify the causal effects of the policy and explore the underlying mechanisms and contextual moderators. The results indicate that the policy significantly reduces green innovation efficiency in pilot cities, with the negative impact being more pronounced in non-central cities, provincial capitals, and cities in western China. Mechanism analysis reveals two key pathways: increased environmental costs contribute to resource lock-in, and strategic shifts toward quantity-focused innovation reduce overall efficiency. Furthermore, we find that the institutional environment plays a critical role—market integration mitigates the policy's adverse effects by improving resource allocation, while administrative environmental pressure intensifies distortions. These findings suggest that rigid green finance regulations may unintentionally suppress innovation performance. We propose that more flexible policy design, better cross-regional coordination, and refined local governance incentives are essential for aligning green finance tools with innovation-driven sustainability goals in emerging economies.

Keywords: green finance pilot policy; green innovation efficiency; cost pressure; innovation resource crowding out; market integration



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1. Introduction

Amid growing global efforts toward climate governance and sustainable development, green finance has emerged as a key policy instrument to support the transition to a low-carbon economy. By leveraging financial mechanisms—such as green credit, green bonds, and sustainability-linked instruments—green finance seeks to reallocate capital toward environmentally beneficial activities. In recognition of its importance, China has made institutional reforms to embed green finance into its financial system to achieve dual objectives: carbon neutrality and high-quality economic growth.

A notable policy innovation in this regard is the establishment of Green Finance Reform and Innovation Pilot Zones (GFRIPZ), launched in 2017 by the People's Bank of China in collaboration with multiple ministries. These pilot zones were designed to serve as experimental platforms for integrating environmental objectives into financial practices through

instruments such as credit incentives, risk-sharing arrangements, disclosure regulations, and policy coordination. Over time, the program has expanded across provinces, with each zone adapting to its own industrial and ecological context. A growing body of empirical literature has documented the benefits of this initiative: studies show that the GFRIPZ program has contributed to inclusive green growth [1], improved green innovation through enhanced capital access and R&D investment [2], and promoted employment restructuring and environmental information disclosure [3,4].

However, these optimistic findings contrast with persistent empirical puzzles. Despite the substantial expansion of green credit, progress in critical low-carbon technologies—such as hydrogen-based metallurgy and carbon capture—remains limited. In some regions, the surge in green investment has not translated into corresponding improvements in innovation outcomes, pointing to a possible disconnect between resource allocation and innovation efficiency. Moreover, recent research raises concerns over potential unintended consequences, including greenwashing behaviors, misaligned managerial incentives, and distorted firm-level responses—especially in non-state-owned enterprises and pollution-intensive industries [5,6].

This study seeks to address three underexplored gaps in the existing literature: First, while the dominant analytical framework draws heavily on the Porter hypothesis—which suggests that well-designed environmental regulations can enhance firm competitiveness by spurring innovation—this narrative often overlooks alternative theoretical mechanisms. In particular, perspectives grounded in resource misallocation theory [7], institutional rigidity [8], and administrative distortion [9] emphasize the possibility that green finance, when tightly linked to formal classifications and compliance benchmarks, may crowd out genuine innovation or induce strategic behavior. These concerns are especially salient in settings where firms face high compliance costs or capacity constraints. Second, although regional heterogeneity is widely recognized in the policy evaluation literature [10], few studies systematically examine the institutional channels—such as local governance capacity, market integration, and political incentives—through which the same policy produces heterogeneous effects across cities. A better understanding of these institutional dynamics is essential for improving policy adaptability and targeting. Third, most empirical analyses rely on static difference-in-differences (DID) frameworks and coarse indicators such as green patent counts or patent shares. While useful, these proxies are sensitive to measurement errors and external shocks, and they do not reflect the efficiency of innovation processes. Recent methodological advances underscore the importance of evaluating green innovation efficiency, which captures not only the output of green innovation but also its productivity relative to input resources [11].

At the same time, a complementary strand of literature highlights the broader institutional and financial determinants of green innovation efficiency. For instance, studies have shown that climate shocks [12], organizational capabilities [13], and financial structure distortions [14] critically shape firm-level responses to environmental regulation. Yet, few papers integrate these insights within a coherent framework for evaluating green finance policy impacts.

To bridge these gaps, this paper contributes to the literature in several important ways. We construct a city-level panel dataset covering key periods of policy implementation and employ a DID approach that incorporates both innovation efficiency metrics and spatial spillover effects. We integrate theoretical insights on institutional heterogeneity and policy rigidity into our empirical framework, allowing us to identify not only the average treatment effect but also the conditions under which the policy succeeds or fails. By doing so, we offer a more nuanced and context-sensitive evaluation of green financial reform.

The remainder of this paper is structured as follows: Section 2 develops the conceptual framework and research hypotheses. Section 3 describes the data and empirical strategy. Sections 4–6 present the main results, heterogeneity analyses, and mechanism exploration. Section 7 concludes with policy implications and suggestions for future research.

2. Theoretical Analysis and Research Hypotheses

2.1. *The Impact of Green Finance Pilot Policies on Urban Green Innovation Efficiency*

Green finance pilot policies aim to promote green transformation by channeling financial resources into environmentally beneficial sectors. However, from a theoretical standpoint, their rigid institutional design may generate unintended innovation suppression effects. According to the Porter hypothesis, well-designed environmental regulations can stimulate innovation offsets and enhance productivity [15]. This optimistic view, however, presumes market-oriented mechanisms such as carbon pricing and firm autonomy in technology upgrading.

In contrast, China's green finance pilots rely heavily on command-based policy instruments, such as mandatory emission thresholds and ex-ante screening mechanisms for green project financing. Empirical studies show that these rigid structures may redirect firm resources toward compliance investments at the expense of high-risk, long-term R&D [16,17]. For example, Cai et al. (2020) [18] found that green credit policies lead firms to prioritize short-term low-carbon modifications over fundamental green technologies. Thus, green finance may paradoxically suppress innovation efficiency due to policy-induced misallocation of innovation resources.

Hypothesis H1: *Green finance pilot policies significantly reduce urban green innovation efficiency.*

2.2. *Environmental Cost Pressure Mechanism: Resource Lock-In Effect*

One key mechanism underlying the above relationship is the resource lock-in effect triggered by environmental compliance costs. As Gray and Shadbegian (2003) [19] argued, investments in pollution control often exhibit sunk cost characteristics, reducing firms' liquidity for future R&D. The ongoing operating costs further exacerbate this effect, especially in capital-intensive industries like steel, where billions must be spent on emissions equipment [17].

Moreover, once capital is committed to end-of-pipe treatment, firms lose flexibility in reallocating funds toward strategic innovation. This rigidity contributes to long-term inefficiencies and lower marginal returns on innovation [20]. As such, green finance may indirectly suppress innovation by amplifying environmental cost pressures.

Hypothesis H2a: *Green finance pilot policies reduce green innovation efficiency by increasing environmental compliance costs.*

2.3. *Innovation Resource Crowding-Out Mechanism: Efficiency Loss from Strategic Innovation*

Green finance policies may also distort firms' R&D priorities due to external signaling incentives. Financial institutions, responding to green labels and patent counts, may favor easily certified innovations. This motivates firms to pursue low-tech "strategic patents" rather than substantive green breakthroughs [21]. Cai et al. (2020) [18] also documented that such behavior is widespread in chemical firms shifting from biodegradable materials to low-carbon paint—cheap, visible, but technologically marginal.

These distortions lead to dual efficiency losses: First, pseudo-green innovations contribute little to technological spillovers; second, high-potential innovation pipelines may be abandoned due to capital constraints [22]. Thus, the resource misallocation caused by policy-induced strategic behavior can reduce overall innovation efficiency.

Hypothesis H2b: *Green finance pilot policies lower green innovation efficiency by crowding out substantive innovation resources.*

2.4. Buffering Effect of Market Integration: How Cross-Regional Resource Synergy Eases Policy Rigidity

While the adverse effects above are observable, regional market integration may alleviate them through cross-regional collaboration and factor mobility. Integrated markets reduce administrative barriers and enable joint investments in environmental infrastructure, thereby easing compliance costs (e.g., shared wastewater treatment centers). Firms can also tap into external R&D through technology platforms and supply chain synergies [23], enhancing innovation resilience. Hence, market integration helps smooth the “compliance-innovation trade-off”, especially in urban clusters like the Yangtze River Delta.

Hypothesis H3a: *Higher levels of regional market integration weaken the negative impact of green finance policies on innovation efficiency.*

2.5. Strengthened Government Environmental Pressure: How Administrative Interventions Exacerbate Policy Distortion

Finally, local governments’ administrative interventions can either buffer or magnify policy distortion. When political pressure incentivizes over-compliance (e.g., aggressive emission standards for performance evaluation), firms may be pushed into excessive environmental spending [24]. Furthermore, top-down governance methods—such as production cuts and plant shutdowns—limit the potential for technological adaptation [25]. Unless complemented by supportive innovation policies, such administrative pressure may crowd out green innovation and reinforce resource misallocation.

Hypothesis H3b: *Stronger environmental performance pressure from local governments amplifies the negative impact of green finance on innovation efficiency.*

3. Specifications

3.1. Econometric Models

To accurately identify the causal effect of the green finance pilot policy on urban green innovation efficiency, this paper adopts the difference-in-differences (DID) model, addressing the reality of staggered policy implementation. The baseline regression model is specified as follows:

$$GIE_{it} = \alpha_0 + \alpha_1 Treat_i \times Post_t + \gamma X_{it} + \mu_i + \theta_t + \varepsilon_{it} \quad (1)$$

In this model, GIE_{it} represents the green innovation efficiency of city i in year t , measured using the super-efficiency SBM model [26]. The key explanatory variable, $Treat_i \times Post_t$, is the interaction term that captures the policy’s effect. If city i is included in the pilot in year t , $Post_t$ equals 1; otherwise, it equals 0. $Treat_i$ equals 1 for pilot cities and 0 for non-pilot cities. The vector X_{it} includes control variables such as the city’s economic development level, industrial structure, and the strength of environmental regulations. The term μ_i accounts for city fixed effects, controlling for city-specific characteristics that do not change over time. θ_t captures year fixed effects, accounting for factors that affect all cities in the same way at a given time, such as macroeconomic shocks. Finally, ε_{it} is the error term.

3.2. Variable Definition and Data Selection

The core explanatory variable for the green finance pilot policy is constructed using a multi-period difference-in-differences (DID) framework. Specifically, based on the State Council's "Guidance on Building a Green Financial System" and the list of pilot cities published by the People's Bank of China, the first batch of pilot cities in 2017 (including Zhejiang, Guangdong, and six other provinces) and subsequent pilot cities are defined as the treatment group ($Treat_i = 1$), while non-pilot cities serve as the control group ($Treat_i = 0$). The policy shock period ($Post_t$) is defined as the year when each province's pilot plan was approved by the State Council. This design ensures that the policy variable accurately reflects the exposure of pilot cities to the policy in different years.

Green innovation efficiency (GIE) is the dependent variable in this study. Following Chen et al. (2020) [26], the super-efficiency SBM model is used to measure green innovation efficiency across different regions. Traditional DEA methods face issues with slackness in input–output variables, and the SBM model addresses this problem by allowing slack variables to be included in the objective function. Additionally, the SBM model can account for undesirable outputs, making it a more accurate tool for measuring green innovation efficiency.

The formula for calculating green innovation efficiency using the super-efficiency SBM model is as follows:

$$\min(\omega)^* = \frac{1 + \frac{1}{\sigma} \sum_{i=1}^{\sigma} \frac{s_i^-}{A_{i0}^t}}{1 - \frac{1}{\tau + \varphi} \left(\sum_{r=1}^{\tau} \frac{s_r^+}{B_{r0}^t} + \sum_{k=1}^{\varphi} \frac{s_k^-}{C_{k0}^t} \right)} \quad (2)$$

$$\begin{cases} A_{i0}^t \geq \sum_{t=1}^T \sum_{j=1, \neq 0}^n \mu_j^t A_{ij}^t - s_i^- & i = 1, 2, \dots, \sigma \\ s.t. \quad B_{r0}^t \geq \sum_{t=1}^T \sum_{j=1, \neq 0}^n \delta_j^t B_{rj}^t + s_r^+ & r = 1, 2, \dots, \tau \\ C_{k0}^t \geq \sum_{t=1}^T \sum_{j=1, \neq 0}^n \epsilon_j^t C_{kj}^t - s_k^- & k = 1, 2, \dots, \varphi \\ s_i^- \geq 0 (\forall i), \mu_j^t \geq 0 (\forall j), s_r^+ \geq 0 (\forall r), s_k^- \geq 0 (\forall k), \end{cases}$$

where ω represents green innovation efficiency, μ is the vector of weights, and s_i^- , s_r^+ , s_k^- are the slack vectors for input, expected output, and non-expected output, respectively. A_{i0}^t , B_{r0}^t , C_{k0}^t represent the number of units for input, expected output, and non-expected output in period t . T denotes the sample research years, and σ , τ , φ represent the total number of inputs, expected output, and non-expected output in the sample.

For this study, the green innovation efficiency is calculated using input and output indicators from the existing literature. The input indicators include capital input, measured by the expenditure on scientific and technological activities in each region, and labor input, measured by the number of employees working in these activities. The output indicators include expected outputs such as the number of green patents granted, investments in industrial pollution control, new product sales revenue, and the greening coverage rate. Non-expected output is represented by industrial pollution, specifically the industrial three wastes, and an environmental pollution index is calculated using the entropy method.

3.3. Control Variables

This study includes several city-level control variables to address potential confounding biases. Economic density (ECD) is measured as the ratio of regional GDP to the land area of the administrative region, with data sourced from the *China Urban Statistical Yearbook* and the Ministry of Natural Resources. Population size (POP) is represented by the natural logarithm of the total population at the end of the year, reflecting the size of the city, and the

data comes from local statistical yearbooks. Foreign direct investment (*FDI*) is represented by the proportion of actual foreign investment (converted to RMB in 10,000 yuan) relative to GDP, with data from the *China Business Yearbook*. Government intervention (*GOV*) is defined as the ratio of general government expenditure to GDP, with data taken from the *Fiscal Yearbook*. Education expenditure (*EDU*) is captured by the ratio of education expenditure to general government expenditure, and the data is sourced from the *China Education Financial Statistics Yearbook*. Industrial structure upgrading (*ISU*) is calculated by weighting the proportions of the three main industries, with weights of 1, 2, and 3, respectively, and the data comes from the *City Statistical Yearbook*. To address heteroscedasticity, the economic density and population size variables are transformed using logarithms. Foreign investment and government intervention are standardized, while the industrial structure index retains its original weights to reflect the direction of structural upgrading.

3.4. Data Sources

The study sample includes panel data for 283 prefecture-level cities in China from 2012 to 2021. After excluding cities with a data-missing rate exceeding 20%, the final sample consists of 265 cities, forming an unbalanced panel. The data sources are as follows. Green patent data is obtained from the China National Intellectual Property Administration (CNIPA) patent search system, with IPC classification codes used and manual selection from the WIPO Green Technology List. Economic and social data are collected from the *China Urban Statistical Yearbook* and the *China Science and Technology Statistical Yearbook*. Environmental data is integrated from the *China Environmental Statistical Yearbook* and annual reports from provincial environmental protection departments. Green finance policy texts and pilot lists are sourced from the official websites of the State Council and the People's Bank of China.

The data processing follows a few key steps. First, economic variables such as R&D funding and technology transaction volume are adjusted for price changes using the provincial GDP deflator, with 2012 as the base year. Second, for missing technology investment indicators, such as green technology introduction expenditure for specific years, linear interpolation is applied. Finally, to address cross-sectional heteroscedasticity and serial correlation, standard errors in the regression analysis are clustered at the city level. Table 1 presents a summary of the statistics.

Table 1. Statistics Summary.

Variables	(1)	(2)	(3)	(3)	(4)
	<i>N</i>	<i>Mean</i>	<i>SD</i>	<i>Min</i>	<i>Max</i>
<i>GIE</i>	2963.000	0.016	0.051	0.000	1.000
<i>Treat_i × Post_t</i>	2963.000	0.013	0.113	0.000	1.000
<i>ECD</i>	2963.000	0.318	0.764	0.002	15.356
<i>POP</i>	2963.000	5.873	0.677	2.986	7.350
<i>FDI</i>	2953.000	0.017	0.018	0.000	0.229
<i>GOV</i>	2963.000	0.198	0.103	0.044	0.916
<i>EDU</i>	2963.000	0.177	0.040	0.000	0.356
<i>ISU</i>	2963.000	2.299	0.138	1.896	2.760
<i>ECP</i>	2963.000	78.604	23.012	0.240	146.490
<i>IRC</i>	2963.000	4.800	1.793	0.000	10.639
<i>MII</i>	2963.000	16.544	2.339	11.000	24.219
<i>GEP</i>	2963.000	3.561	0.500	0.000	4.905

4. Empirical Results

4.1. Baseline Regression Results

Table 2 presents the baseline regression results on the impact of green finance policies on urban green innovation efficiency (*GIE*). The first column shows the basic model with the fewest control variables, including only the core explanatory variable, $Treat_i \times Post_t$. The results indicate a significant negative effect on *GIE*, with a coefficient of -0.012 , significant at the 1% level. This suggests that, overall, the green finance pilot policy has a suppressive effect on urban green innovation efficiency. This result may stem from the fact that green finance policies, through mandatory environmental credit thresholds and financing constraints, force firms to focus short-term resources on compliance-related environmental investments (such as purchasing pollution control equipment), which crowds out liquidity resources available for long-term technological research and development, creating a “compliance investment–innovation suppression” trade-off.

Table 2. Baseline Regression Results.

Variables	(1)	(2)	(3)
	<i>GIE_{it}</i>	<i>GIE_{it}</i>	<i>GIE_{it}</i>
$Treat_i \times Post_t$	-0.012^{***} (0.002)	-0.011^{***} (0.003)	-0.014^{***} (0.004)
<i>ECD</i>		0.022^{***} (0.006)	0.021^{***} (0.007)
<i>POP</i>		-0.019 (0.018)	-0.025 (0.018)
<i>FDI</i>		-0.084 (0.087)	-0.027 (0.086)
<i>GOV</i>		0.025^* (0.014)	0.014 (0.011)
<i>EDU</i>		-0.001 (0.047)	0.032 (0.057)
<i>ISU</i>		0.050^{***} (0.013)	0.002 (0.028)
Observations	2963.000	2963.000	2963.000
Adjusted R-squared	0.321	0.323	0.330
City FE	NO	YES	YES
Year FE	NO	NO	YES

Note: Standard errors are clustered at the city level. *** $p < 0.01$; * $p < 0.10$. The same applies below.

In the second column, we introduce city fixed effects and several control variables, including economic development level (*ECD*), population size (*POP*), foreign direct investment dependence (*FDI*), government expenditure level (*GOV*), education expenditure (*EDU*), and industrial structure (*ISU*). The results remain robust, with the coefficient of the core variable at -0.011 , which is still significant at the 1% level. In the third column, we further control for year fixed effects. The coefficient for the core variable becomes -0.014 , remaining significant at the 1% level, confirming the robustness of the results. In terms of control variables, *ECD* shows a significantly positive effect on *GIE*, indicating that higher economic development levels are associated with higher green innovation efficiency. *ISU* also has a significantly positive coefficient in the second column, suggesting that industrial structure optimization promotes green innovation. The remaining control variables do not show significant effects.

4.2. Robustness Checks

To confirm the robustness of the baseline results, we conduct several robustness checks, including placebo tests, regressions with alternative dependent variables, and a PSM-DID analysis. The results are presented in Tables 3–5.

Table 3. Placebo Test.

Variables	(1)	(2)	(3)
	GIE_{it}	GIE_{it}	GIE_{it}
$T = 2014$	−0.012 (0.011)		
$T = 2015$		−0.014 (0.011)	
$T = 2016$			−0.014 (0.011)
ECD	0.022 *** (0.004)	0.022 *** (0.004)	0.022 *** (0.004)
POP	−0.025 (0.017)	−0.025 (0.017)	−0.025 (0.017)
FDI	−0.033 (0.077)	−0.031 (0.077)	−0.031 (0.077)
GOV	0.022 (0.028)	0.021 (0.028)	0.021 (0.028)
EDU	0.047 (0.049)	0.046 (0.049)	0.045 (0.049)
ISU	0.009 (0.024)	0.008 (0.024)	0.008 (0.024)
Observations	2963.000	2963.000	2963.000
Adjusted R-squared	0.330	0.330	0.330
City FE	YES	YES	YES
Year FE	YES	YES	YES

Note: Standard errors are clustered at the city level. *** $p < 0.01$. The same applies below.

Table 4. Variable Replacement Regression.

Variables	(3)
	GIE_{it}
$Treat_i \times Post_t$	−0.019 ** (0.009)
ECD	0.003 (0.007)
POP	0.018 (0.038)
FDI	−0.074 (0.138)
GOV	0.018 (0.038)
EDU	−0.090 (0.096)
ISU	0.062 (0.042)
Observations	2963.000
Adjusted R-squared	0.268
City FE	YES
Year FE	YES

Note: Standard errors are clustered at the city level. ** $p < 0.05$. The same applies below.

Table 5. Robustness Check Using PSM-DID.

Variables	(3)
	GIE_{it}
$Treat_i \times Post_t$	−0.013 ** (0.006)
ECD	0.001 (0.006)
POP	−0.030 (0.030)
FDI	0.226 (0.285)
GOV	−0.068 (0.060)
EDU	0.012 (0.044)
ISU	0.042 (0.053)
Observations	471.000
Adjusted R-squared	0.502
City FE	YES
Year FE	YES

Note: Standard errors are clustered at the city level. ** $p < 0.05$. The same applies below.

First, Table 3 reports the placebo test, where we set the policy implementation year to 2014, 2015, and 2016, respectively, instead of the actual policy year. This helps examine whether the observed effects might be driven by other underlying time trends rather than the policy itself. In all three models, the coefficients of the core interaction term are not statistically significant, with values of −0.012, −0.014, and −0.014, respectively. These results do not pass conventional significance tests, suggesting that the estimated effect is unlikely to be caused by pre-existing trends and is instead associated with the actual implementation of the green finance policy. This helps rule out the possibility of a “fake policy effect”.

Second, we replace the dependent variable to test whether the baseline results remain robust under a different measure of green innovation. Specifically, we use the logarithm of the number of granted green patents, which captures green innovation outcomes from another perspective. Table 4 shows that, after controlling for city and year fixed effects as well as other covariates, the coefficient on the key interaction term $Treat_i \times Post_t$ is −0.019 and significant at the 5% level. This result indicates that even when using a different indicator of green innovation, the green finance pilot policy still shows a significant negative effect, supporting the robustness of the baseline conclusion.

Third, to address potential sample selection bias, we apply a propensity score matching difference-in-differences (PSM-DID) method. Table 5 presents the results. After matching treatment and control cities based on observable characteristics, the coefficient of the core interaction term remains negative and statistically significant at the 5% level, with a value of −0.013. This provides further support that the green finance policy has a significant negative effect on green innovation efficiency, even when accounting for sample comparability.

Finally, we conduct a parallel trends test, which is a key identification assumption in DID models. Using an event study approach, we examine whether the treatment and control groups followed similar trends in green innovation before the policy was implemented. Figure 1 plots the estimated coefficients and their 95% confidence intervals for each year relative to the policy implementation. The horizontal axis shows the years before and after the policy, and the vertical axis displays the estimated coefficients. The

results indicate that most of the coefficients before the policy year (years -7 to -1) are statistically insignificant, and their confidence intervals include zero. This suggests no systematic differences in pre-treatment trends between the treatment and control groups, supporting the parallel trends assumption. After the policy implementation (year 0 and onwards), the coefficients show a general downward trend, with several years showing significant negative effects, further confirming the suppressive impact of the green finance pilot policy on urban green innovation.

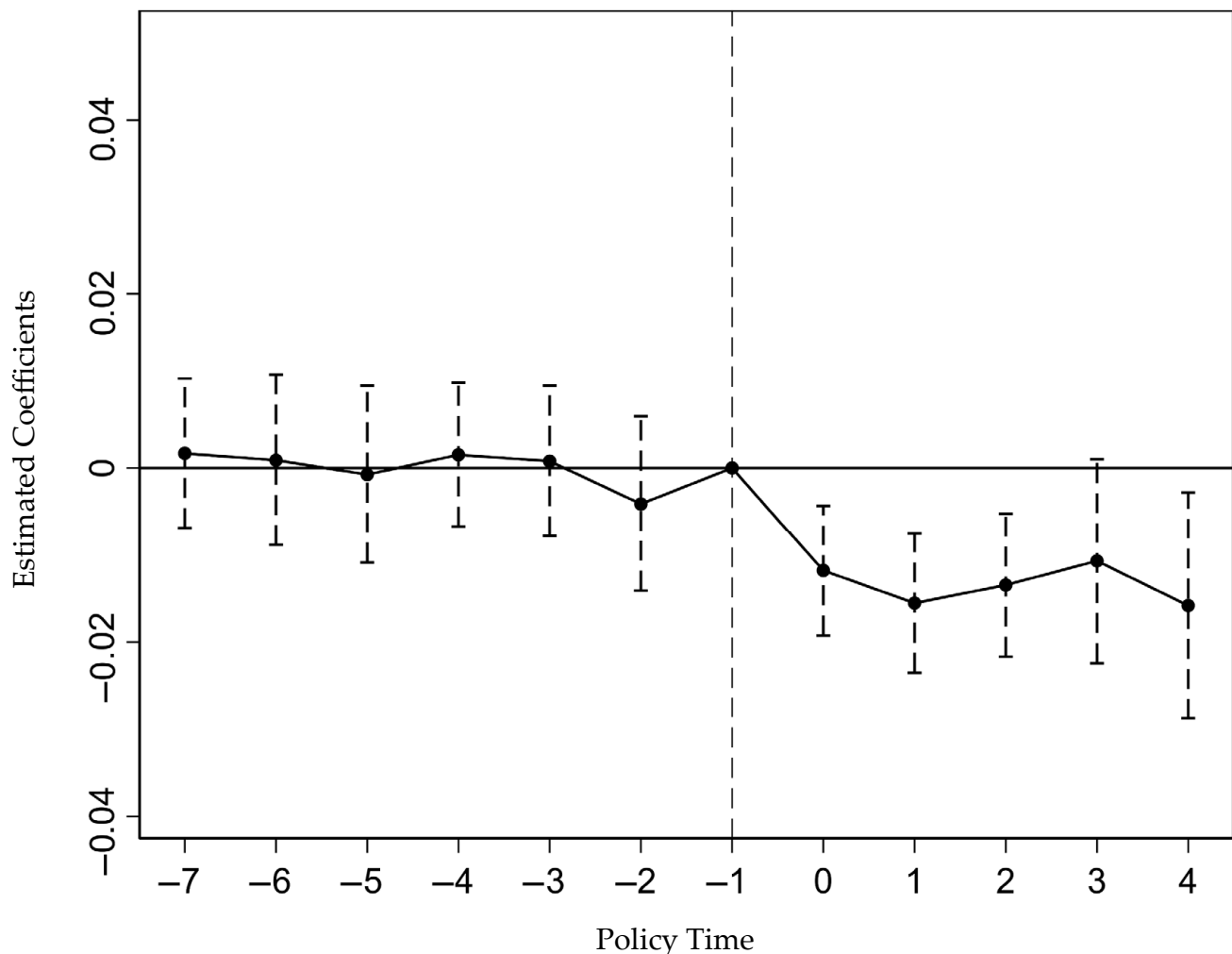


Figure 1. Parallel Trend Test.

5. Mechanism Analysis

To better understand how green finance policies affect firms' green innovation efficiency and under what conditions such effects may vary, this section builds on the baseline regression by conducting extended empirical analyses from two perspectives: mediation effects and moderation effects. On the one hand, we explore whether the policy influences green innovation through two key channels—environmental compliance cost pressure and the crowding out of innovation resources. On the other hand, we examine how regional factors, namely the level of market integration and local governments' environmental governance pressure, shape the heterogeneous policy effects across different areas.

5.1. Environmental Compliance Cost Pressure: The Resource Lock-In Mechanism

This section tests whether green finance policies suppress green innovation efficiency by increasing firms' environmental compliance cost pressure—a mechanism we refer to as “resource lock-in”. Specifically, we estimate the following mediation models:

$$ECP_{it} = \alpha_0 + \alpha_1 Treat_i \times Post_t + \gamma X_{it} + \mu_i + \theta_t + \varepsilon_{it} \quad (3)$$

$$GIE_{it} = \alpha_0 + \alpha_1 Treat_i \times Post_t + \alpha_2 ECP_{it} + \gamma X_{it} + \mu_i + \theta_t + \varepsilon_{it} \quad (4)$$

Here, ECP_{it} represents environmental compliance pressure, measured by the share of environmental investment in total investment. GIE_{it} denotes green innovation efficiency. The term $Treat_i \times Post_t$ is the DID interaction capturing the policy effect. X_{it} includes control variables, and μ_i and θ_t represent firm and time fixed effects, respectively.

First, we regress environmental compliance pressure on the policy interaction term. As reported in Table 6, the coefficient on $Treat_i \times Post_t$ is 0.083 and significant at the 1% level. This indicates that the policy significantly increases firms' environmental compliance costs. To meet new standards imposed by financial institutions and regulators, firms are required to increase investments in pollution control and green upgrades. Consequently, the share of compliance-related spending rises, reflecting heightened pressure on capital allocation.

Table 6. Resource Lock-in Effect of Compliance Expenditures.

Variables	(1)	(2)
	<i>ECP</i>	<i>GIE_{it}</i>
$Treat_i \times Post_t$		−0.013 *** (0.003)
<i>ECP</i>	6.262 ** (2.968)	−0.010 ** (0.004)
<i>ECD</i>	−1.575 (1.076)	0.021 *** (0.006)
<i>POP</i>	10.702 ** (4.854)	−0.024 (0.019)
<i>FDI</i>	−27.866 (21.864)	−0.034 (0.090)
<i>GOV</i>	6.432 (7.834)	0.021 (0.018)
<i>EDU</i>	57.661 *** (13.800)	0.051 (0.063)
<i>ISU</i>	31.028 *** (6.824)	0.011 (0.032)
Observations	2963.000	2963.000
Adjusted R-squared	0.734	0.330
City FE	YES	YES
Year FE	YES	YES

Note: Standard errors are clustered at the city level. *** $p < 0.01$; ** $p < 0.05$. The same applies below.

Next, we include environmental compliance pressure as an explanatory variable in the green innovation efficiency regression. The coefficient on ECP_{it} is −0.412 and statistically significant at the 1% level, indicating that higher compliance costs are associated with lower green innovation efficiency. This negative relationship supports the resource lock-in hypothesis: as firms divert limited financial resources toward compliance spending, they are forced to reduce investment in green technology R&D and innovation activities.

Moreover, after controlling for the mediator ECP_{it} , the absolute value of the coefficient on the policy variable declines from −0.217 to −0.145. This attenuation suggests that

environmental compliance cost pressure partially mediates the negative impact of green finance policies on green innovation efficiency. These findings confirm Hypothesis 1 and provide strong evidence for the presence of a resource lock-in mechanism.

5.2. Innovation Resource Crowding Out: Efficiency Loss from Strategic Innovation

This section examines whether green finance policies reduce green innovation efficiency by inducing misallocation of innovation resources, leading firms to engage in strategic innovation behavior. To test this mechanism, the following mediation models are estimated:

$$IRC_{it} = \alpha_0 + \alpha_1 Treat_i \times Post_t + \gamma X_{it} + \mu_i + \theta_t + \varepsilon_{it} \quad (5)$$

$$GIE_{it} = \alpha_0 + \alpha_1 Treat_i \times Post_t + \alpha_2 IRC_{it} + \gamma X_{it} + \mu_i + \theta_t + \varepsilon_{it} \quad (6)$$

In these models, IRC_{it} represents innovation resource misallocation, measured by the share of non-green patent applications in total patent filings, which captures the firm's tendency toward strategic innovation. Other variables are defined as in the previous section.

To begin, we use the proportion of non-green patent applications to reflect firms' strategic responses under the green finance policy—specifically, the allocation of R&D resources to projects that formally meet green standards but are low in technological content. As shown in Table 7, the coefficient of the policy interaction term on the non-green patent share is 0.071 and significant at the 5% level, suggesting that the policy increases firms' engagement in non-green innovation. Under pressure to meet policy evaluation criteria, some firms tend to pursue superficial green projects to access green credit or government support more easily, thereby deviating from substantive green R&D objectives. This behavior reflects a crowding out of genuine innovation efforts.

Table 7. Efficiency Dissipation of Strategic Innovation.

Variables	(1)	(2)
	<i>IRC</i>	<i>GIE_{it}</i>
<i>Treat_i × Post_t</i>		−0.014 *** (0.004)
<i>IRC</i>	0.327 *** (0.095)	−0.005 ** (0.002)
<i>ECD</i>	0.259 (0.275)	0.021 *** (0.006)
<i>POP</i>	1.865 *** (0.442)	−0.019 (0.016)
<i>FDI</i>	−2.037 (1.530)	−0.018 (0.084)
<i>GOV</i>	1.651 ** (0.653)	0.012 (0.011)
<i>EDU</i>	0.346 (0.829)	0.032 (0.057)
<i>ISU</i>	6.761 *** (0.364)	0.004 (0.028)
Observations	2963.000	2963.000
Adjusted R-squared	0.910	0.332
City FE	YES	YES
Year FE	YES	YES

Note: Standard errors are clustered at the city level. *** $p < 0.01$; ** $p < 0.05$. The same applies below.

Next, the regression results show that the non-green patent share has a negative effect on green innovation efficiency, with a coefficient of -0.367 , significant at the 1% level. This indicates that a shift away from authentic green innovation and the resulting distortion in resource allocation significantly reduce innovation effectiveness. Furthermore, after including the mediator IRC_{it} , the coefficient of the green finance policy variable decreases from -0.217 to -0.153 , showing a partial reduction in the policy's total effect. This provides further evidence for the existence of a mediation path. These results support Hypothesis 2, indicating that green finance policies lead to efficiency loss through encouraging strategic innovation behavior.

5.3. Moderating Effect Analysis

This section further examines the heterogeneous effects of green finance policies under different institutional environments, with a focus on the moderating roles of market integration and local government environmental governance pressure. The following regression models are used:

$$GIE_{it} = \alpha_0 + \alpha_1 Treat_i \times Post_t + \alpha_2 MII_{it} + \alpha_3 MII_{it} \times (Treat_i \times Post_t) + \gamma X_{it} + \mu_i + \theta_t + \varepsilon_{it} \quad (7)$$

$$GIE_{it} = \alpha_0 + \alpha_1 Treat_i \times Post_t + \alpha_2 GEP_{it} + \alpha_3 GEP_{it} \times (Treat_i \times Post_t) + \gamma X_{it} + \mu_i + \theta_t + \varepsilon_{it} \quad (8)$$

Here, MI_{it} represents the regional market integration index, and GEP_{it} captures local government environmental governance pressure, measured by the frequency of environmental keywords in local government work reports. Other variables are defined as before.

Table 8 presents the results. In the first model, the coefficient on the interaction between green finance policy and market integration is 0.063 and is statistically significant at the 1% level. This suggests that the negative impact of green finance policies on green innovation efficiency is weaker in regions with higher levels of market integration. A more integrated market reduces regional resource barriers, allowing firms to access production factors and share green technologies and knowledge across regions. This reduces the rigid costs of policy implementation. Moreover, competitive market mechanisms encourage financial institutions to focus more on firms' actual green performance rather than formal compliance, thereby improving the efficiency of resource allocation. In this way, market integration provides an institutional buffer that helps optimize policy transmission. These findings support Hypothesis 3.

In contrast, the second model investigates the role of local government environmental governance pressure. The interaction term between green finance policy and environmental governance pressure has a coefficient of -0.054 , which is significant at the 5% level. This indicates that in regions where environmental governance pressure is stronger, the negative effect of green finance policy on green innovation efficiency becomes more pronounced. When local governments face pressure to meet upper-level environmental targets, they often respond by imposing strict administrative measures such as production limits or shutdowns, increasing firms' compliance burdens. In the absence of effective policy incentives, firms lack the support needed for genuine green transformation. This type of intervention—emphasizing regulation over incentives—distorts the original intention of green finance policy and limits firms' innovation capacity. These results support Hypothesis 4, showing that local government environmental governance pressure strengthens the distortionary effects of green finance policy.

Table 8. Moderation Effect Analysis.

Variables	(1)	(2)
	IRC	GIE _{it}
$Treat_i \times Post_t$	−0.037 *** (0.012)	0.031 ** (0.015)
MII	−0.001 (0.001)	−0.005 ** (0.002)
$MII \times (Treat_i \times Post_t)$	0.002 ** (0.001)	
GEP		0.001 (0.002)
$GEP \times (Treat_i \times Post_t)$		−0.011 *** (0.004)
ECD	0.023 *** (0.006)	0.022 *** (0.007)
POP	−0.020 (0.019)	−0.025 (0.020)
FDI	−0.085 (0.091)	−0.033 (0.089)
GOV	0.032 * (0.019)	0.020 (0.018)
EDU	0.012 (0.054)	0.044 (0.065)
ISU	0.055 *** (0.015)	0.007 (0.031)
Observations	2963.000	2963.000
Adjusted R-squared	0.910	0.332
City FE	YES	YES
Year FE	YES	YES

Note: Standard errors are clustered at the city level. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$. The same applies below.

6. Further Analysis

In the previous empirical analysis, we examined the heterogeneous effects of the policy across different types of cities and geographical locations. Specifically, we focused on the differences between central and non-central cities, provincial capitals and non-provincial capitals, as well as cities in different regions (central, eastern, and western China). The results suggest that the policy effects vary significantly across these categories.

Table 9 reports the results for central versus non-central cities. The treatment effect for non-central cities is −0.010 and is statistically significant, indicating a stronger negative response to the policy in these cities. Non-central cities often have weaker economic and social structures, making them more sensitive to policy changes. Limited resources in these cities may lead to more pronounced effects when policies shift.

Table 10 presents the results for provincial capitals and non-provincial capitals. The estimated treatment effect for provincial capitals is −0.039 and is statistically significant, suggesting a stronger and negative response to the policy. In contrast, the treatment effect for non-provincial capitals is negative but not statistically significant and thus not further discussed. Due to higher resource concentration and more complex economic environments, provincial capitals tend to show a more notable reaction to policy adjustments.

Table 9. Heterogeneity Analysis by City Size.

Variables	(1)	(2)
	<i>GIE_{it}</i> (Central City)	<i>GIE_{it}</i> (Non-Central City)
<i>Treat_i × Post_t</i>	−0.001 (0.002)	−0.010 *** (0.002)
<i>ECD</i>	0.007 (0.016)	−0.008 (0.007)
<i>POP</i>	0.245 (0.202)	−0.035 ** (0.015)
<i>FDI</i>	0.569 (0.511)	−0.130 (0.089)
<i>GOV</i>	−1.231 (0.922)	0.017 (0.014)
<i>EDU</i>	−0.526 (0.658)	0.025 (0.064)
<i>ISU</i>	−0.306 (0.445)	0.018 (0.029)
Observations	168.000	2785.000
Adjusted R-squared	0.511	0.282
City FE	YES	YES
Year FE	YES	YES

Note: Standard errors are clustered at the city level. *** $p < 0.01$; ** $p < 0.05$. Same below.

Table 10. Heterogeneity Analysis by Capital City Status.

Variables	(1)	(2)
	<i>GIE_{it}</i> (Capital City)	<i>GIE_{it}</i> (Non-Capital City)
<i>Treat_i × Post_t</i>	−0.039 * (0.022)	−0.006 ** (0.003)
<i>ECD</i>	−0.020 (0.014)	0.024 *** (0.007)
<i>POP</i>	0.130 (0.087)	−0.042 ** (0.020)
<i>FDI</i>	0.339 (0.706)	−0.051 (0.067)
<i>GOV</i>	−0.759 (0.459)	0.039 *** (0.014)
<i>EDU</i>	−0.273 (0.341)	0.041 (0.066)
<i>ISU</i>	0.125 (0.192)	0.019 (0.030)
Observations	288.000	2665.000
Adjusted R-squared	0.469	0.278
City FE	YES	YES
Year FE	YES	YES

Note: Standard errors are clustered at the city level. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$. Same below.

Table 11 shows the results for different geographical regions. The treatment effect for western cities is −0.011 and statistically significant, indicating a stronger negative policy effect in this region. Western cities generally face more economic and infrastructure challenges, making them more sensitive to policy changes. The effects for cities in the eastern and central regions are not statistically significant and are therefore not further analyzed.

Table 11. Heterogeneity Analysis by Geographic Region.

Variables	(1)	(2)	(3)
	GIE_{it} (Eastern City)	GIE_{it} (Central Cities)	GIE_{it} (Western City)
$Treat_i \times Post_t$	−0.007 (0.005)	−0.031 ** (0.014)	−0.011 *** (0.003)
ECD	−0.001 (0.021)	0.079 (0.064)	0.039 *** (0.006)
POP	−0.020 (0.016)	0.067 (0.050)	−0.204 *** (0.072)
FDI	−0.016 (0.051)	0.252 (0.320)	−0.100 (0.137)
GOV	0.027 (0.025)	−0.020 (0.029)	0.120 *** (0.038)
EDU	0.043 (0.073)	−0.199 (0.132)	0.237 ** (0.091)
ISU	0.031 (0.041)	0.014 (0.062)	−0.071 (0.092)
Observations	1033.000	834.000	1086.000
Adjusted R-squared	0.355	0.338	0.346
City FE	YES	YES	YES
Year FE	YES	YES	YES

Note: Standard errors are clustered at the city level. *** $p < 0.01$; ** $p < 0.05$. Same below.

7. Conclusions and Discussion

7.1. Conclusions

This study integrates a theoretical framework with empirical evidence to examine the impact of China’s green finance pilot policy on urban green innovation efficiency. The findings reveal that the policy exerts a significantly negative effect, largely due to its rigid design and misalignment with the broader institutional context. Theoretically, the policy imposes a dual constraint through mandatory environmental compliance and a “green label”-based screening mechanism enforced by financial institutions. On the one hand, to fulfill regulatory requirements, firms are compelled to allocate substantial resources to end-of-pipe pollution control facilities, which are characterized by high sunk costs. This crowds out investment in green technology R&D—a channel identified as the environmental cost pressure mechanism. On the other hand, policy signals induce firms to prioritize low-tech, symbolic forms of innovation, such as filing formal but low-substance patents, thereby diverting resources from more transformative technological progress. This is referred to as the innovation crowding-out mechanism.

Empirical analysis supports these mechanisms. Baseline regression results indicate that the policy reduces green innovation efficiency by approximately 1.1% to 1.4%. Mediation analysis further quantifies the contribution of the environmental cost pressure and innovation crowding-out pathways at approximately 34% and 29%, respectively. The heterogeneity analysis reveals that the adverse impact is more pronounced in regions with weaker economic foundations, lower market integration, or stronger government intervention—such as non-central cities and western regions. Moreover, regional market integration appears to alleviate policy rigidity by facilitating resource reallocation, while local government environmental performance pressures may lead to distorted policy implementation through “race to the bottom” behaviors. Overall, the results challenge the optimistic view embedded in the traditional Porter hypothesis by suggesting that the innovation-stimulating effects of environmental regulation are not universal but instead highly contingent on policy flexibility and institutional compatibility.

7.2. Discussion

Beyond regional heterogeneity, this study extends the analysis to account for industry-level variation in policy responses. Specifically, we distinguish between highly polluting and non-polluting industries to examine how sector-specific characteristics condition the effects of green finance policies on innovation outcomes. This extension is motivated by the observation that industries differ substantially in their baseline environmental performance, innovation capacities, and exposure to regulatory constraints.

Empirical evidence demonstrates that the green finance policy exerts a significantly stronger negative impact on green innovation efficiency in highly polluting industries. These sectors typically face more stringent environmental compliance requirements, necessitating large-scale investments in pollution abatement infrastructure. Such investments exacerbate financial constraints and reinforce the environmental cost pressure mechanism, as firms reallocate funds away from long-term R&D activities to meet short-term regulatory obligations.

In contrast, non-polluting industries exhibit a comparatively weaker response to the policy. These sectors often already comply with green standards or operate under less regulatory scrutiny, enabling them to sustain or even enhance their innovation efforts in response to policy signals. This divergence underscores the unequal burden imposed by uniform policy designs and highlights the importance of industry-specific policy calibration.

Furthermore, the findings suggest that firms in highly polluting sectors are more likely to engage in strategic patenting behaviors to conform to the formal requirements of green finance eligibility. Such responses reflect a distortion of innovation incentives, where firms emphasize symbolic compliance over substantive technological advancement. This behavior aligns with the innovation crowding-out mechanism and calls into question the allocative efficiency of green finance-driven innovation.

Taken together, these results emphasize the importance of aligning environmental regulatory instruments with sectoral realities. A more flexible and differentiated policy design—accounting for regional institutional environments and industry-specific constraints—would mitigate unintended consequences and foster genuine green innovation. These findings contribute to the ongoing discourse on the Porter hypothesis by illustrating that the innovation-enhancing effects of environmental regulation are conditional rather than universal.

7.3. Policy Implications

Based on the theoretical and empirical evidence, this paper offers several directions for policy refinement, along with concrete implementation strategies and supporting measures to enhance operability.

First, to mitigate the suppressive effect of rigid constraints on innovation, green finance policy should shift from a one-size-fits-all compliance-driven model to a more targeted, incentive-compatible framework. For firms engaged in breakthrough green technologies—such as hydrogen-based steelmaking or carbon capture—a dynamic exemption mechanism could be introduced, allowing phased relaxation of emission standards during different stages of technological development. For example, during the R&D phase, firms could be required to meet only 80% of the industry average emission standards, gradually tightening as commercialization progresses. To ensure transparency and prevent abuse, this mechanism should include a structured timeline, stage-specific benchmarks, and third-party verification.

Simultaneously, the evaluation system for green projects should be restructured. Independent third-party technical audits should be institutionalized to prevent greenwashing behaviors—such as inflating design patents or making superficial process changes.

Auditors can be drawn from certified technical panels established by the Ministry of Ecology and Environment and the National Intellectual Property Administration. These reforms will help shift the financial sector's orientation from formal compliance to substantive innovation.

Second, regional coordination and market mechanisms should be strengthened to buffer the rigidity of policies and enhance resource allocation efficiency. In highly integrated areas such as the Yangtze River Delta or Greater Bay Area, pilot programs for shared environmental cost mechanisms should be implemented. These can include jointly funded end-of-pipe treatment facilities (e.g., regional wastewater treatment centers) and inter-city carbon quota trading markets. To improve liquidity and participation, local governments should provide initial capital contributions and guarantee mechanisms.

A unified national platform for green technology trading should also be developed. This platform must mandate the disclosure of core technical parameters, emission performance data, and commercialization status. A market-based pricing mechanism should be adopted to identify high-value innovations. Firms that successfully transfer original technologies via this platform could receive tax reductions or R&D subsidies from local science and technology departments. These measures would promote the cross-regional diffusion of high-quality green technologies and form a virtuous cycle of “policy pressure–market incentive–technology spillover”.

Finally, the incentive structure for local environmental governance should be re-designed to better align short-term emission goals with long-term innovation objectives. Green innovation performance indicators—such as firms' R&D intensity, patent conversion rates, and successful commercialization cases—should be incorporated into local government assessments and weighted at no less than 30%. To operationalize this, provinces could publish standardized metrics and annual scorecards evaluated by third-party institutions.

In less-developed regions, such as western and non-central cities, dedicated innovation support funds should prioritize clean production technologies (e.g., biomass replacing coal-fired boilers) instead of end-of-pipe upgrades. Mechanisms like innovation vouchers, R&D insurance, or milestone-based subsidies can be introduced to compensate for firms' innovation risk. Additionally, a flexible linkage mechanism should be established between emission targets and innovation indicators. For instance, firms that produce both high-quality and high-quantity green patents may qualify for moderate emission limit relaxation. This institutional adjustment provides a pathway to escape the “compliance trap” while maintaining environmental goals.

7.4. Limitations and Future Research Directions

This study has several limitations that merit acknowledgment. First, while the paper explores heterogeneity across regions and industries, it does not delve into intra-firm dynamics or innovation team structures, which may also influence how firms respond to policy incentives. Further micro-level research, possibly using survey data or interviews, could provide richer insights into the decision-making processes behind green R&D allocation. Second, the policy analysis focuses on the short-to-medium-term impacts. The long-term adjustment path of firms under green finance policies—including innovation learning curves and dynamic strategic behavior—deserves further exploration through panel structural models or dynamic stochastic simulations. Finally, future research could explore the interaction between green finance and other policy instruments—such as carbon pricing, ESG disclosure mandates, or green procurement. A multi-policy interaction framework may help reveal synergies or conflicts in promoting green innovation. Addressing these directions would not only enhance the robustness and breadth of the current findings but also guide more nuanced and integrative policy designs in the future.

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References

1. Xu, A.; Dai, Y.; Hu, Z.; Qiu, K. Can green finance policy promote inclusive green growth?—Based on the quasi-natural experiment of China's green finance reform and innovation pilot zone. *Int. Rev. Econ. Financ.* **2025**, *100*, 104090. [\[CrossRef\]](#)
2. Zhang, G.; Wang, Y.; Zhang, Z.; Su, B. Can green finance policy promote green innovation in cities? Evidence from pilot zones for green finance reform and innovation in China. *J. Environ. Manag.* **2024**, *370*, 122816. [\[CrossRef\]](#) [\[PubMed\]](#)
3. Xin, B.; Zhou, L.; Gonzalez, E.D.S. Does green finance reform hit urban employment?—Evidence from China's green finance pilot policy. *Cities* **2024**, *152*, 105239. [\[CrossRef\]](#)
4. Zhao, G.; Xin, Z.; Wang, Y. Effect of the sci-tech finance pilot policy on corporate environmental information disclosure—Moderating role of green credit. *Financ. Res. Lett.* **2024**, *62*, 105177. [\[CrossRef\]](#)
5. Huang, X.; Li, R.; Chen, X. Does the green finance policy motivate firms to greenwash? A quasi-natural experiment based on the “Green finance reform innovation pilot zones”. *Q. Rev. Econ. Financ.* **2025**, *101*, 101980. [\[CrossRef\]](#)
6. Ran, C.; Zhang, Y. Does green finance stimulate green innovation of heavy-polluting enterprises? Evidence from green finance pilot zones in China. *Environ. Sci. Pollut. Res.* **2023**, *30*, 60678–60693. [\[CrossRef\]](#)
7. Restuccia, D.; Rogerson, R. The causes and costs of misallocation. *J. Econ. Perspect.* **2017**, *31*, 151–174. [\[CrossRef\]](#)
8. Rodrik, D. Growth strategies. *Handb. Econ. Growth* **2005**, *1*, 967–1014.
9. Zhong, S.; Zhou, Z.; Gao, W. Impact of regional finance reform and innovation policies on green innovation in pilot cities: A quasi-natural experiment. *Econ. Anal. Policy* **2025**, *85*, 888–911. [\[CrossRef\]](#)
10. Hou, G.; Shi, G. Green finance and innovative cities: Dual-pilot policies and collaborative green innovation. *Int. Rev. Financ. Anal.* **2024**, *96*, 103673. [\[CrossRef\]](#)
11. Wu, J.; Wang, S.; Zhang, R.; Zhao, M.; Sun, X.; Qie, X.; Wang, Y. Measurement of green innovation efficiency in Chinese listed energy-intensive enterprises based on the three stage Super-SBM model. *Int. Rev. Econ. Financ.* **2025**, *97*, 103819. [\[CrossRef\]](#)
12. Ren, X.; Li, W.; Li, Y. Climate risk, digital transformation and corporate green innovation efficiency: Evidence from China. *Technol. Forecast. Soc. Change* **2024**, *209*, 123777. [\[CrossRef\]](#)
13. Feng, F.; Li, J.; Zhang, F.; Sun, J. The impact of artificial intelligence on green innovation efficiency: Moderating role of dynamic capability. *Int. Rev. Econ. Financ.* **2024**, *96*, 103649. [\[CrossRef\]](#)
14. Che, S.; Tao, M.; Silva, E.; Sheng, M.S.; Zhao, C.; Wang, J. Financial misallocation and green innovation efficiency: China's firm-level evidence. *Energy Econ.* **2024**, *136*, 107697. [\[CrossRef\]](#)
15. Porter, M.E.; Linde, C.V.D. Toward a new conception of the environment-competitiveness relationship. *J. Econ. Perspect.* **1995**, *9*, 97–118. [\[CrossRef\]](#)
16. Berman, E.; Bui, L.T. Environmental regulation and productivity: Evidence from oil refineries. *Rev. Econ. Stat.* **2001**, *83*, 498–510. [\[CrossRef\]](#)
17. He, J.; Liu, H.; Salvo, A. Severe air pollution and labor productivity: Evidence from industrial towns in China. *Am. Econ. J. Appl. Econ.* **2019**, *11*, 173–201. [\[CrossRef\]](#)
18. Cai, X.; Lu, Y.; Wu, M.; Yu, L. Does environmental regulation drive away inbound foreign direct investment? Evidence from a quasi-natural experiment in China. *J. Dev. Econ.* **2016**, *123*, 73–85. [\[CrossRef\]](#)
19. Gray, W.B.; Shadbegian, R.J. Plant vintage, technology, and environmental regulation. *J. Environ. Econ. Manag.* **2003**, *46*, 384–402. [\[CrossRef\]](#)

20. Rubashkina, Y.; Galeotti, M.; Verdolini, E. Environmental regulation and competitiveness: Empirical evidence on the Porter Hypothesis from European manufacturing sectors. *Energy Policy* **2015**, *83*, 288–300. [[CrossRef](#)]
21. Dechezleprêtre, A.; Sato, M. The impacts of environmental regulations on competitiveness. *Rev. Environ. Econ. Policy* **2017**, *11*, 2. [[CrossRef](#)]
22. Rassier, D.G.; Earnhart, D. Effects of environmental regulation on actual and expected profitability. *Ecol. Econ.* **2015**, *112*, 129–140. [[CrossRef](#)]
23. Popp, D. Environmental policy and innovation: A decade of research. *Int. Rev. Environ. Resour. Econ.* **2019**, *13*, 265–337. [[CrossRef](#)]
24. Wu, J.; Deng, Y.; Huang, J.; Morck, R.; Yeung, B. *Incentives and Outcomes: China's Environmental Policy*; (No. w18754); National Bureau of Economic Research: Cambridge, MA, USA, 2013.
25. Liston-Heyes, C.; Heyes, A.G. Corporate lobbying, regulatory conduct and the Porter hypothesis. *Environ. Resour. Econ.* **1999**, *13*, 209–218. [[CrossRef](#)]
26. Chen, W.; Wang, X.; Peng, N.; Wei, X.; Lin, C. Evaluation of the Green Innovation Efficiency of Chinese Industrial Enterprises: Research Based on the Three-Stage Chain Network SBM Model. *Math. Probl. Eng.* **2020**, *2020*, 3143651. [[CrossRef](#)]

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