Green Finance Policy and Urban Pollution and Carbon Emission Reduction:Impact Mechanisms and Spatial Spillover Effects

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ABSTRACT

Global climate change and environmental pollution have become critical constraints on sustainable development. As an essential institutional arrangement reconciling economic growth with environmental protection, green finance (GF) has emerged as a core driver of the global green transition. Using China's 2017 establishment of the Green Finance Reform and Innovation Pilot Zones as a quasi-natural experiment, this study constructs a panel of 273 Chinese cities from 2008 to 2023. It applies a difference-in-differences model and a spatial Durbin model to systematically assess the direct, indirect, and spatial spillover effects of the green finance policy (GFP) on urban pollution and carbon emission reduction (PCR).The results indicate that GFP significantly advances PCR, with stronger effects observed in eastern and western regions, old industrial bases, and resource-based cities. The mechanism analysis reveals that GFP promotes PCR by enhancing the quantity of green innovation, reducing energy consumption intensity, and promoting green energy efficiency, while industrial structure upgrading exerts a temporary masking effect. The spatial analysis further shows that while GFP significantly enhances local PCR, it exerts a negative spillover effect on neighboring cities, with the influence confined within 300 kilometers and gradually weakening with distance. This study uncovers the internal logic through which GFP facilitates pollution and carbon emission reduction at the city level, offering robust empirical evidence and providing practical policy implications for developing economies aiming to enhance GF systems and advance sustainable development.

Keywords: Green finance policy; Urban pollution and carbon emission reduction; Quasi-natural experiment; Spatial spillover effects

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1. Introduction

Rising global climate risks and environmental pollution pose critical constraints to sustainable development. The 2015 Paris Agreement has catalyzed a worldwide commitment to low-carbon development and green transformation. The OECD (2017) views green finance (GF) as an important mechanism for balancing economic growth and environmental protection, while the World Bank (2021) similarly emphasizes that GF has become a vital public good in achieving the coordinated governance of pollution control and climate mitigation. Against this backdrop, China is at a critical stage of advancing economic restructuring in pursuit of its "dual carbon" goals. To address the dual constraints of economic transformation and ecological governance, China established the Green Finance Reform and Innovation Pilot Zones (GFRIPZ) in 2017 to explore effective institutional approaches for mobilizing financial support for promoting the green transition. This policy not only represents an institutional innovation within the financial system that supports ecological civilization, but also provides a "Chinese solution" for developing countries to reconcile economic growth with emission reduction. However, key questions remain to be answered: Can the green finance policy (GFP) achieve synergistic effects on urban pollution and carbon emission reduction (PCR)? What are their underlying mechanisms and spatial spillover patterns? Clarifying these issues is of great significance for enhancing the green financial system and advancing regional green development.

Existing research has predominantly analyzed the impact of GF on carbon emissions and environmental pollution in isolation (Ahsan Iqbal et al., 2025; Du et al., 2025; Li et al., 2022; Ran and Zhang, 2023; Zhao et al., 2024), while research on the synergistic effects of PCR has been insufficiently explored. Particularly in the context of developing countries, variations in institutional settings and market structures complicate policy transmission mechanisms. Therefore, it is essential to build upon China's policy practices to empirically examine the environmental effects of GFP and to uncover its transmission mechanisms and the spatial attenuation of its effects across regions.

In this context, the paper uses GFRIPZ as a quasi-natural experiment to systematically evaluate the direct impacts, mechanisms, and spatial effects of GFP on PCR.The main contributions of the paper are as follows: (1) Regarding measurement, based on data from cities, this study constructs an PCR index by combining the environmental pollution index with carbon emissions, accurately capturing the essence of "coordinated emission reduction" and effectively augmenting existing indicators.(2) It explores the transmission mechanisms of GFP through three pathways: green innovation (GI), industrial structure (INS), and energy conservation and consumption reduction (ECCR), by distinguishing between the quantity and quality of GI, the upgrading and rationalization of INS, and the differential effects of energy consumption intensity and green energy efficiency.(3) By incorporating spatial effects into the analytical framework, the study identifies the spatial spillovers and geographic attenuation of GFP, offering new empirical evidence to understand the diffusion mechanisms of GF in developing economies.

2. Literature review

The concept of pollution and carbon emission reduction originated from the need for coordinated governance under the dual challenges of global environmental pollution and climate change, with its connotation evolving from long-term practices in pollution control and the global consensus on climate governance. Its essence lies in achieving synergistic benefits between environmental pollution control and greenhouse gas emission reduction. In recent years, academia has generally regarded pollution and carbon emission reduction as a key factor in regional green development and has conducted systematic studies on aspects such as the measurement of pollution and carbon reduction and the emission reduction effects of GF.

2.1 Measurement studies on pollution and carbon emission reduction

In the quantitative assessment of pollution and carbon emission reduction, the academic community has accumulated abundant research achievements, with measurement approaches exhibiting considerable diversity. A widely used approach assesses the level of PCR based on the direct measurement of CO_2, SO_2, or PM2.5 emissions (Dong et al., 2022; Liu et al., 2024; Tang et al., 2025). Another approach regards the pollution system and carbon emission system as two independent yet co-evolving subsystems. Standardized indicator systems are constructed for each and weighted to obtain composite scores. The coupling degree model is then applied to measure their interaction intensity, and a coordination degree function is used to evaluate their synergistic level, thereby comprehensively characterizing pollution and carbon emission reduction (Xiang et al., 2025; Yue and Han, 2025; Zhu et al., 2024). Meanwhile, some studies evaluate pollution and carbon emission reduction level by selecting multiple indicators such as particulate matter concentration, sulfur dioxide, soot and dust, wastewater, and carbon dioxide, and constructing comprehensive scores (Xiao et al., 2024; Zhu et al., 2025).

2.2 The pollution-reduction effects of GF

Studies examining the impact of GF on pollution control generally operate at three analytical scales: macro, meso, and micro. Evidence at the macro level indicates that GF improves regional environmental quality by lowering emissions of SO_2, NO_x, and particulate matter (Li and Xu, 2024). However, these effects show marked regional heterogeneity (Li and Xu, 2024), with emission-reduction benefits spreading from local to neighboring regions and diminishing with distance (Zhou et al., 2025). Cross-country studies also reveal that GF development effectively reduces ecological footprints and enhances environmental performance (Khan et al., 2023), though its environmental effects exhibit nonlinearity and stage-dependent characteristics (Criscuolo and Menon, 2015). At the meso level, GF improves air quality by strengthening environmental regulation and promoting INS upgrading (Lan et al., 2023). Its emission-reduction effects mainly stem from reduced energy intensity and enhanced levels of green technology (Li and Yong, 2025). Further studies indicate that green credit plays a critical role in constraining the expansion of energy-intensive industries and optimizing INS, effectively curbing pollution emissions in the secondary sector (Wen et al., 2021). Meanwhile, GF promotes pollution control and industrial green transformation by attracting foreign investment and restricting financing for polluting enterprises, thereby facilitating the treatment of industrial "three wastes" and ozone (Fan et al., 2025). At the micro level, GF effectively lowers the emission intensity of highly polluting firms by imposing credit constraints and offering financing incentives, with more pronounced effects observed in state-owned and large firms (Wang et al., 2025).

2.3. The carbon-reduction effects of GF

The role of GF in carbon emission reduction has been widely verified, with existing studies primarily focusing on two dimensions: green financial instruments and green financial policies. Regarding financial instruments, different types of GF tools exhibit varying impacts on carbon reduction, among which green credit plays the most significant role (Nie et al., 2025). It achieves emission reduction by promoting the adoption of low-carbon technologies (X. Lei et al., 2025; Y. Li et al., 2025), optimizing the industrial investment structure (Zhang et al., 2022), and constraining energy-intensive industries.Moreover, green fund investments significantly enhance firms' resources, innovation, and structural effects, thereby contributing to emissions reduction (X. Li et al., 2025). However, the carbon reduction effects of GF instruments display notable regional heterogeneity and spatial dependence (Q. Li et al., 2025). At the policy level, early studies suggest that GFP strengthens environmental constraints on enterprises and promote their green transition through financing penalties and investment restriction mechanisms (Meng et al., 2025). Recent studies based on quasi-natural experiments further demonstrate that the establishment of GFRIPZ has significantly reduced urban carbon emissions (Jin et al., 2026). These effects are primarily driven by mechanisms such as INS optimization (Xian-Chun et al., 2023) and GI (Hu et al., 2023).

2.4. Summary

A review of the existing literature indicates that several limitations remain unaddressed: (1) The measurement system of pollution and carbon emission reduction has not yet been unified, limiting the comparability and explanatory power of research findings. (2) Existing studies predominantly focus on either carbon emissions or environmental pollution individually, lacking a systematic exploration of the effects of GFP on pollution and carbon emission reduction. (3) The identification of spatial spillover effects of GFP remains insufficient, with limited understanding of their cross-regional transmission and dynamic impact processes. In response to these gaps, this study constructs a PCR indicator system that captures the interaction between environmental pollution and carbon emissions. It systematically examines the direct, indirect, and spatial spillover effects of GFP on PCR, offering novel theoretical insights and empirical evidence to inform the optimization of GFP and enhance regional ecological governance.

3. Theoretical analysis and research hypotheses

Against the backdrop of the global green transitions, GFP has become a key driver of PCR. Fig. 1 illustrates the impact of GFP on PCR. The direct effect indicates that GFP can significantly promote PCR. The indirect effect shows that GFP promotes PCR through GI,INS and ECCR. Moreover, the spatial effect is reflected in that GFP drives the cross-regional transmission of PCR through spillover or siphon effects.

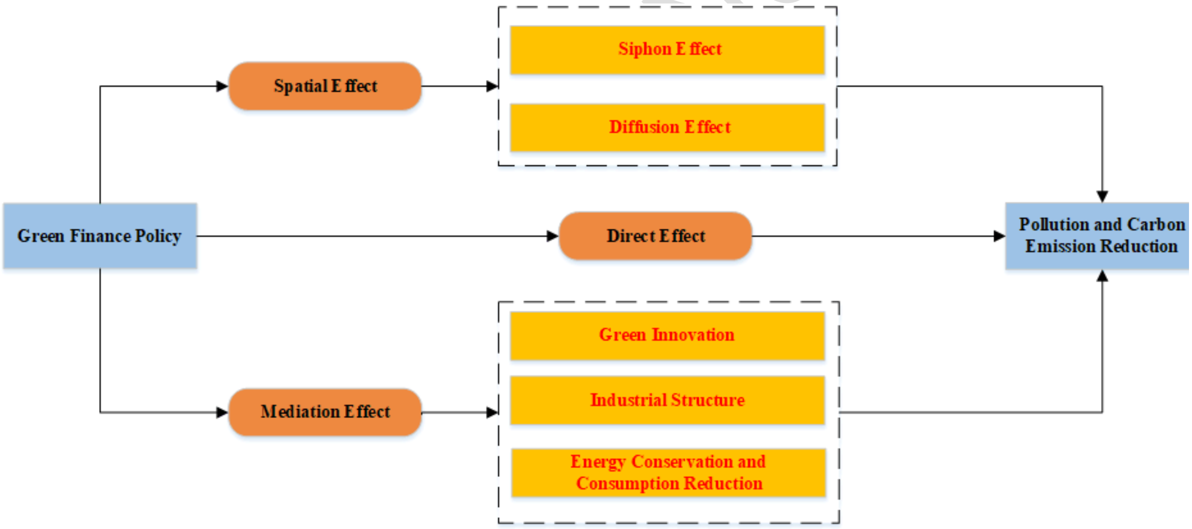

Fig. 1. The mechanism of GFP impact on pollution and carbon emission reduction

3.1. Direct impact of GFP on PCR

GFP represents an important institutional arrangement to address environmental externalities. It requires the financial sector to incorporate potential environmental risk factors into investment and financing decisions and to integrate environment-related potential returns and risk costs into regular financial operations. This mechanism internalizes the financing costs of polluting entities, corrects negative externalities, and ultimately improves environmental quality (Lee et al., 2023). Specifically, first, green subsidy policies, as a form of government intervention, provide direct financial support to green enterprises, thereby effectively reducing their initial investment costs. This financial support not only encourages enterprises to invest in green projects but also directs market resources toward green industries, alleviating funding shortages in green project financing. Second, tax incentives, as an encouraging policy instrument, reduce the economic burden on green enterprises, aiming to stimulate production and investment activities with positive environmental externalities (Pan and Lin, 2025). Together with the binding “polluter pays principle,” they constitute a complementary system within environmental economic policy. Third, GFRIPZ, representing a combination of “top-down” and “bottom-up” GFP, aim to generate replicable and scalable experiences. By emphasizing green economic development and aligning with policy support, they continuously improve GF system, innovate green financial products, and alleviate financing constraints, thereby strengthening environmental improvement outcomes (Du et al., 2025).

Accordingly, the following hypothesis is formulated:

H1: GFP can significantly promote PCR.

3.2. Mediating effect of GFP on PCR

3.2.1. GFP, GI, and PCR

GFP improves the financing environment for enterprises within a region, reduces the uncertainty risks of green projects, and enhances regional information transparency and credit accessibility, thereby fostering an ecosystem conducive to GI (H. Lei et al., 2025). On one hand, under the guidance of GFP, financial institutions prioritize allocating capital to projects involving clean production, energy efficiency, emission-reduction, and low-carbon technology projects, thereby supporting regional innovation investment from the perspective of capital supply (He et al., 2025). On the other hand, GF, through mechanisms of environmental information disclosure and credit evaluation, enhances the financial system’s ability to identify and price green technology risks, thereby enabling regional innovation activities to obtain long-term and low-cost financing more effectively.

GI drives PCR through three dimensions: technology, knowledge, and competition. At the technological level, it reduces pollution and carbon emissions at the source by improving energy efficiency, optimizing production processes, and substituting clean energy (Shang et al., 2022). At the knowledge level, it promotes the cumulative evolution of low-carbon technologies through technology diffusion, knowledge spillovers, and cross-regional learning. At the competitive level, it builds firms’ environmental competitive advantages, triggering imitation and follow-up behaviors within industries and forming a “green competition diffusion” mechanism that achieves broader collaborative emission reduction (Zhang et al., 2020).

Accordingly, the following hypothesis is formulated:

H2: GFP promotes PCR through GI.

3.2.2. GFP, INS, and PCR

GFP reshapes capital flows and investment structures through institutional arrangements such as capital supply, risk pricing, and information disclosure, thereby exerting a systemic influence on INS adjustment (Gao et al., 2023). In terms of capital supply, GF strengthens credit constraints on high-pollution and high-energy-consuming industries while lowering the financing costs for green industries, guiding capital to shift from traditional polluting sectors toward low-carbon and efficient domains. In terms of risk pricing, GF introduces differentiated mechanisms in asset pricing and credit access, channeling financial resources toward high value-added and low-pollution industries, and promoting the scale expansion of green manufacturing and technology-intensive sectors. Regarding information disclosure, GF enhances transparency within industries by improving financial standard systems, strengthening environmental information disclosure, and refining third-party certification mechanisms. This enhances financial institutions' ability to assess firms' environmental performance and long-term potential, thereby optimizing capital allocation and facilitating INS upgrading toward high-end development.

INS is a core structural driver of regional pollution and carbon emissions (Tian et al., 2019). Emissions are largely concentrated in energy-intensive industries of the secondary sector, in contrast to the service-led tertiary sector, which produces relatively modest direct emissions. Therefore, the upgrading of INS can effectively reduce overall emission intensity. Meanwhile, rational adjustments within the secondary industry, shifting the industrial focus from energy-intensive sectors toward green manufacturing, further reduce emissions per unit of output (Gu et al., 2022). The growth of high value-added, technology-intensive sectors enhances total factor productivity and optimizes resource allocation, which in turn reduces pollutant and carbon emissions per unit of output. Moreover, low-carbon transformation and energy efficiency improvement within the tertiary sector can also significantly reduce pollutant emissions and energy consumption.

GFP can promote PCR by optimizing INS; however, its effectiveness is not guaranteed under all circumstances. When institutional supply is insufficient and the product system is underdeveloped, green capital fails to accumulate effectively, and funds tend to flow toward traditional industries with higher short-term returns. Corporate "greenwashing" behaviors further exacerbate resource misallocation (Shi et al., 2023). Moreover, inconsistent standards in GFP and low-quality information disclosure can lead to adverse selection and moral hazard, thereby weakening the policy's effectiveness in curbing PCR (Lin and Hong, 2022).

Accordingly, the following hypothesis is formulated:

H3a: GFP promotes PCR through the optimization of INS.

H3b: GFP hinders PCR through distortions in INS.

3.3.3. GFP, ECCR, and PCR

GFP influences urban energy systems through two dimensions, energy substitution and energy efficiency improvement, thereby driving urban ECCR (Guo et al., 2023). In terms of energy substitution, GFP reduces the financing costs of clean energy projects, effectively mitigating the financing constraints associated with their "high investment and long cycle" characteristics. This expands investment in renewable energy sources such as wind, solar, hydropower, and nuclear power, thereby promoting a cleaner energy structure (Calcaterra et al., 2024; Meckling et al., 2022). In terms of energy efficiency improvement, GFP leverages preferential interest rates on green credit, specialized financing from green bonds, and risk-sharing mechanisms to significantly lower the financial threshold for enterprises engaged in energy-saving retrofitting and green R&D. This encourages firms to upgrade equipment, optimize production processes, and develop green technologies, ultimately manifesting at the city level as continuous improvements in green total factor energy efficiency (Yu et al., 2024).

ECCR represent a key pathway to advancing the synergy between PCR in cities (Degirmenci et al., 2025). First, the transition toward a cleaner energy structure can directly reduce pollutant and carbon emissions. The emission intensity of clean energy in both production and consumption stages is significantly lower than that of fossil fuels; thus, increasing its share directly reduces the overall levels of urban pollutants and greenhouse gas emissions. Second, diversifying the energy structure helps strengthen the systemic resilience of environmental governance. Increasing the proportion of renewable energy reduces dependence on high-carbon energy sources, mitigates emission concentration risks, and improves the stability and sustainability of the energy system (Campiglio et al., 2023). Finally, optimizing the energy structure lays the foundation for long-term green development. The green transition of the energy structure gradually internalizes environmental costs within economic operations, helping to balance current emission reduction tasks with future sustainability goals and realize the coordinated optimization of the environment and the economy.

Accordingly, the following hypothesis is formulated:

H4: GFP promotes PCR through ECCR.

3.3. Spatial effect of GFP on PCR

The impact of GFP on PCR is not confined within geographical boundaries but instead exhibits significant spatial dependence and spillover characteristics through various interregional linkages (Zhang et al., 2023). The fundamental causes lie in two aspects. On the one hand, pollutants and carbon emissions exhibit strong cross-regional transfer and diffusion characteristics due to their negative externalities and the incomplete nature of environmental governance information. On the other hand, the diffusion and competition effects of GFP often transcend individual jurisdictions, spreading to geographically adjacent or economically interconnected regions.

From the perspective of positive mechanisms, GFP demonstrates a pronounced “diffusion effect.” First, at the technological level, GFP alleviates the financing constraints faced by clean technologies and emission-reduction processes, enabling leading cities to achieve equipment upgrading and process optimization ahead of others, thereby accelerating the diffusion of green technologies (Xu et al., 2023). Second, at the institutional level, pilot cities within GFRIPZ establish stricter standards for information disclosure, classified investment guidance, and performance evaluation mechanisms. These experiences diffuse to neighboring regions through the “pilot, demonstration, promotion” policy learning pathway, fostering regional convergence in environmental regulation intensity and governance models.

From the perspective of negative mechanisms, GFP may also trigger a “competition effect.” When a region strengthens GFP and environmental regulations, the financing and compliance costs for polluting projects increase. In the absence of effective regional coordination and constraint mechanisms, energy-intensive and highly polluting firms may relocate to regions with looser policies, resulting in a “pollution haven” effect and spatial transfer of emissions (Liu et al., 2022).

However, such diffusion and competition effects do not extend infinitely across geographical space but exhibit certain attenuation boundaries. On one hand, an increase in geographic distance intensifies financial information asymmetry, making financial institutions more inclined to provide services to geographically proximate firms. On the other hand, the widespread existence of market segmentation and local protectionism, such as administrative boundary policies, weakens the cross-regional transmission capacity of GFP, thereby causing its spatial spillover effects to diminish gradually with increasing distance.

Accordingly, the following hypothesis is formulated:

H5: GFP exerts spatial spillover effects on PCR, and due to the objective constraints of geographical distance, GFP exhibits spatial attenuation characteristics.

4. Research design

4.1. Models

4.1.1. Difference-in-Differences (DID) model

To accurately assess the impact of GFP on PCR, this study constructs a Difference-in-Differences (DID) model to examine the policy effects on cities, as follows:

$$lnPCR_{it} = \beta_0 + \beta_1 did_{it} + \beta_2 Control_{it} + \gamma_t + \lambda_i + \varepsilon_{it} \quad (1)$$

In equation (1), $\ln PCR_{it}$ denotes PCR index of city *i* in year *t*; $did_{it} = treat_i \times time_t$ indicates whether the policy is implemented in city *i* during year *t*; Controlit represents the control variables; γ_t, λ_i, and ε_{it} denote the time fixed effect, city fixed effect, and random disturbance term, respectively.

4.1.2. Mediation effect model

To further examine the mechanism through which GFP affects PCR, this study constructs the following model with reference to Jiang (2022) recommendation on the mediation effect model:

$$MV_{it} = \theta_0 + \theta_1 did_{it} + \theta_1 Control_{it} + \gamma_t + \lambda_i + \varepsilon_{it} \tag{2}$$

In Equation (2), MV stands for the mediating variable, including GI, INS, and ECCR.

4.1.3. Spatial econometric model

To capture the spatial spillover effect, a spatial difference (SDID) model was further constructed to evaluate the impact of GFP on PCR, as below:

$$\begin{aligned} lnPCR_{it} = \beta_0 + \rho \boldsymbol{W} lnPCR_{it} + \phi_0 did_{it} + \phi_1 \boldsymbol{W} X_{it} + \vartheta_0 Control_{it} + \\ \vartheta_1 \boldsymbol{W} Control_{it} + \gamma_t + \lambda_i + \mu_{it} \end{aligned} \tag{3}$$

$$\mu_{it} = \lambda \boldsymbol{W} \mu_{it} + \varepsilon_{it} \tag{4}$$

In Equation (3) and (4), $\boldsymbol{W}$ denotes the spatial weight matrix, ρ represents the spatial autoregressive coefficient, and λ, ϑ_1, and ϕ_1 indicate the spatial autocorrelation coefficients. When conditions $\rho \neq 0$, $\phi_1 = 0$, $\vartheta_1 = 0$, and $\lambda = 0$ are satisfied, the model becomes a spatial lag model; when $\rho = 0$, $\phi_1 = 0$, $\vartheta_1 = 0$, and $\lambda \neq 0$ are met, it corresponds to a spatial error model; and when $\rho \neq 0$, $\phi_1 \neq 0$, $\vartheta_1 \neq 0$, and $\lambda = 0$ are fulfilled, it is a spatial Durbin model (SDM). Given the close linkage between GFP and geographic distance, as well as the strong influence of spatial proximity on carbon and pollution transfers, this study utilizes a geographic distance matrix in the spatial econometric analysis.

4.2. Research variables

4.2.1. PCR index

The index of PCR is obtained by multiplying the environmental pollution index and carbon emissions. PCR in this paper is an inverse burden indicator; a lower value indicates better pollution and carbon emission reduction performance.The environmental pollution index, constructed following Yang et al. (2019), is derived via an entropy-weighting procedure using three pollutants: sulfur dioxide, smoke and dust, and wastewater discharge. When both the environmental pollution index and carbon emissions are at high levels, the PCR index shows a significant nonlinear upward trend (Zhong et al., 2024). Compared with linear additive indicators, the interaction term better reflects the compound nature of environmental pressure and the nonlinear superposition between pollution and carbon emissions. This design is consistent with the "common-source hypothesis" of carbon and pollution, aligns with the holistic and systemic requirements of coordinated PCR governance, and also echoes the theoretical propositions of collaborative governance (Ayres and Walter, 1991).

4.2.2. GFP

GFP is proxied by an interaction term between a dummy variable indicating pilot cities ($treat_i$) and a time dummy for the post-policy period ($time_t$), that is, $did_{it}=treat_i \times time_t$. This study exploits GFRIPZ established in 2017 as a quasi-natural experiment.

4.2.3. Mechanism variables

(1) GI. Drawing on prior literature (Li and Lin, 2025; Wang et al., 2022), this study constructs two indicators of GI. The quantity of GI is proxied by the number of green utility-model patent applications per 10,000 population, while the quality dimension is captured by the number of green invention patent applications per 10,000 population.

(2) INS. Following Zhu et al. (2019), INS upgrading is proxied by the ratio of value added in the tertiary sector to that in the secondary sector. In addition, INS rationalization is captured by the Theil index, consistent with the approach adopted by (Zheng et al., 2021).

(3) ECCR. Due to the unavailability of complete city-level data on total energy consumption—and given the strong correlation between electricity use and overall energy demand—this study adopts the ratio of electricity consumption to regional GDP as a proxy for energy intensity, following Hankinson and Rhys (1983). Consistent with Meng and Qu (2022), labor, capital, and energy are considered as input factors, regional GDP is treated as a desirable output, and industrial sulfur dioxide emissions, industrial particulate emissions, and industrial wastewater discharges are incorporated as undesirable outputs. The SBM Malmquist–Luenberger index is then applied to evaluate green energy efficiency across cities.

4.2.4. Control variables

To control for other determinants of PCR, this study incorporates several covariates identified in prior research (Chen et al., 2025; Yin et al., 2024). Economic development level is measured by the logarithm of regional GDP (lngdp). Infrastructure development level is captured by the ratio of total fixed asset investment to regional GDP (infr). Urbanization level is represented by the share of permanent urban residents in the total population (urban). Population density is defined as the number of residents per unit of land area (den). Openness level is proxied by the ratio of total imports and exports to regional GDP (open). Government intervention is measured by the ratio of education and science expenditure to regional GDP (gov). Human capital level is proxied by the number of students enrolled in regular higher education institutions relative to the year-end total population (edu).

4.3. Sample selection and data sources

A total of ten cities have been designated as GFRIPZ pilot cities. Since Lanzhou New Area and Chongqing were approved only recently, including them may fail to capture the lagged effects of the policy on PCR; thus, they are excluded from the analysis. Furthermore, due to data limitations, Hami and Jinchang are also omitted. The final sample covers 273 Chinese cities over the period from 2008 to 2023. The main data sources include *the China Urban Statistical Yearbook* and CNRDS, supplemented by data from EPS and official publications of the National Bureau of Statistics. Missing observations are handled using interpolation. It should be noted that city-level carbon emissions and energy-related indicators are partly derived from database-based estimates rather than direct official measurements. Therefore, potential measurement errors may exist. However, the same data sources and construction methods are applied consistently to both treatment and control cities, which helps reduce systematic bias in the DID estimation. Table 1 presents the descriptive statistics for all variables.

As shown in the table, the urban pollution and carbon reduction indicator has a sample mean of 11.727, a standard deviation of 1.789, a minimum value of 2.688, and a maximum value of 17.125, indicating substantial differences across cities in pollution reduction and carbon mitigation; the descriptive statistics of the remaining variables are broadly consistent with those reported in the existing literature (Hu, 2023), suggesting that the variable selection and statistical results in this study are reasonable.

Table 1
Descriptive statistical results

variable name	variable symbol	Obs	Mean	Std. dev	Min	Max
PCR index	lnPCR	4368	11.7270	1.7893	2.6883	17.1246
GFP	did	4368	0.0128	0.1125	0.0000	1.0000
Economic development level	lngdp	4368	16.5693	0.9929	13.5383	19.9729
Infrastructure development level	infr	4368	1.0078	0.7604	0.0031	12.4459
Urbanization level	urban	4368	4.5454	15.8052	13.1400	99.8000
Population density	den	4368	4.2969	3.1769	0.0500	30.0500
Openness level	open	4368	0.2297	0.4035	0.0000	5.4218
Government intervention	gov	4368	0.1564	0.0850	0.0332	0.9110
Human capital level	edu	4368	0.0203	0.0253	0.0000	0.1870

To avoid multicollinearity among variables, which may affect the accuracy of the research results, this study used the variance inflation factor (VIF) test to examine whether multicollinearity existed among the variables; as shown in Table 2, the mean VIF of the main variables was 1.37 and the maximum value was 2.04, both far below the empirical threshold of 10 (O'brien, 2007), indicating that the interference of multicollinearity can be ignored.

Table 2
Multicollinearity test results

Variable	did	lngdp	infr	urban	den	open	gov	edu	mean value
VIF	1.04	2.04	1.18	1.1	1.6	1.19	1.46	1.34	1.37

5. Empirical results

5.1. Baseline regression result

Table 3 presents the estimated effects of GFP on PCR. Columns (1)–(4) show that the coefficient of GFP remains significantly negative across specifications with and without control variables, while its magnitude changes only slightly. This provides initial evidence in support of Hypothesis 1. Column (5) further reports the results based on 500 bootstrap replications, and the coefficient of GFP remains significantly negative, confirming the robustness of the estimates. Although the signs of several control variables, including infrastructure development level, government intervention, and human capital level, vary across model specifications, the direction and statistical significance of the GFP coefficient remain relatively stable. Overall, the findings indicate that GFP significantly promotes PCR, which is consistent with the conclusions of Ahsan Iqbal et al. (2025).

Table 3
Baseline regression results

	(1)	(2)	(3)	(4)	(5)
Variable	lnPCR	lnPCR	lnPCR	lnPCR	Bootstrapped 500 times
did	-0.983***	-0.356***	-0.636***	-0.457***	-0.579***
	(0.147)	(0.129)	(0.146)	(0.127)	(0.167)
lngdp			0.097***	1.022***	1.111***
			(0.037)	(0.079)	(0.039)
infr			-0.195***	0.075***	-0.330***
			(0.023)	(0.022)	(0.031)
urban			-0.008***	-0.009***	-0.006***
			(0.001)	(0.004)	(0.001)
den			0.000	-0.001***	-0.001***
			(0.000)	(0.000)	(0.000)
open			0.623***	0.409***	0.096*
			(0.069)	(0.072)	(0.057)
gov			-3.570***	1.057***	-2.925***
			(0.314)	(0.382)	(0.324)
edu			-4.112**	-1.444	2.385**
			(1.719)	(1.873)	(1.091)
Constant	11.740***	11.940***	10.816***	-4.198***	-5.088***
	(0.097)	(0.043)	(0.579)	(1.279)	(0.637)
City FE	×	√	×	√	√
Year FE	×	√	×	√	√
N	4368	4368	4368	4368	4368
R^2	0.011	0.280	0.294	0.323	0.449

Note: Standard errors are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Same notation applies to the tables below.Column (5) reports bootstrap-based estimates with 500 resampling replications based on the specification in Column (4).

5.2. Parallel trend test

The validity of the Difference-in-Differences (DID) framework hinges on the parallel trend assumption. To examine whether this condition holds, this study employs the event-study specification developed by Jacobson et al. (1993), which is formulated as follows:

$$lnPCR_{it} = \beta_0 + \beta_k did_{i0+k} + \beta_2 Control_{it} + \gamma_t + \lambda_i + \varepsilon_{it} \tag{5}$$

In Equation (5), $did_{i0+k} = treat_i \times after_t$, where *after* is a year dummy variable and k represents the difference between each year and 2017. The definitions of the remaining variables are the same as those presented in Equation (1).

Given the limited number of observations in the four years prior to and six years following policy implementation, this study groups the four pre-policy years into period –4 and the six post-policy years into period 6. Fig. 2 illustrates the results of the parallel trend test, showing that all pre-treatment coefficients are statistically insignificant. This suggests that no systematic differences existed between the treatment and control cities before the introduction of GFP, thereby validating the parallel trend assumption.

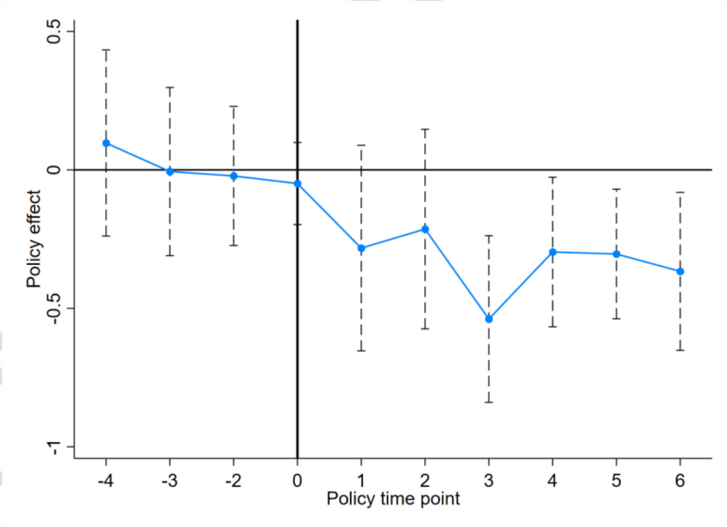

Fig. 2. Differences in urban pollution and carbon reduction before and after the implementation of GFP.

5.3. Placebo test

(1) City placebo test. To mitigate the possibility that the baseline DID estimates are influenced by unobserved omitted variables, this study conducts a placebo test following Jirón et al. (2021) and Zhao et al. (2025). A group of placebo treatment cities is randomly assigned, and the baseline DID model is re-estimated 500 times. Fig. 3 presents the distribution of the resulting coefficients and their p-values. The placebo coefficients are centered around zero and appear approximately normally distributed, with the vast majority

of p-values above the 10% significance level. In contrast, the true GFP coefficient lies well outside the zero-centered distribution and differs significantly from the placebo estimates, indicating that the estimated policy effect is unlikely to arise from random assignment. These findings reinforce the robustness and credibility of the DID results.

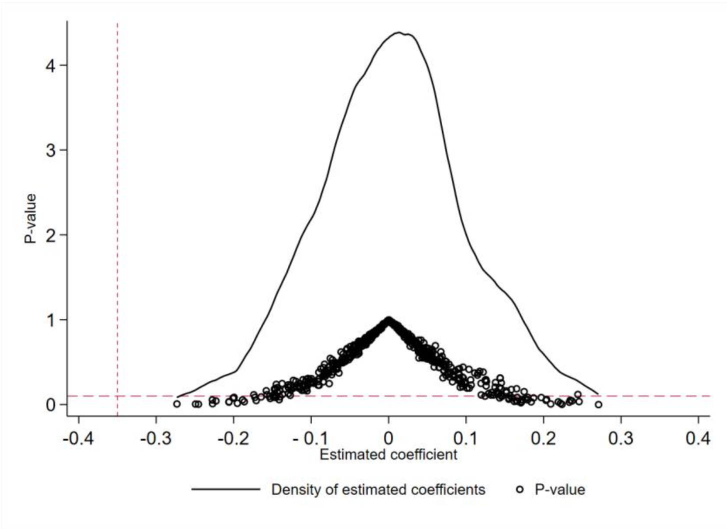

Fig. 3. Placebo test.

(2) Temporal placebo test. To ensure that the estimated PCR effects are not driven by time trends shared by both the treatment and control cities, this study conducts a falsification test by shifting the policy implementation year forward by four years, assigning 2013 as a hypothetical implementation date. As reported in Column (1) of Table 4, the coefficient of the advanced policy variable becomes statistically insignificant, implying the absence of systematic temporal differences between pilot and non-pilot cities before the true policy took effect. This result further corroborates that GFP has genuinely contributed to the improvement of PCR.

5.4. Robustness tests

5.4.1 PSM-DID test

To mitigate potential endogeneity issues arising from sample self-selection bias, this study employs the Propensity Score Matching Difference-in-Differences (PSM-DID) approach, using both 1:1 nearest-neighbor matching and kernel matching methods. As reported in Columns (2) and (3) of Table 4, the coefficients of GFP remain significantly negative under both matching approaches, indicating that GFP continues to exert a significant promoting effect on PCR.

5.4.2 Shortened time window

Changes in the observation period may influence regression outcomes. To test this, the first and last four years of the sample period are excluded, reducing the observation window to 2012–2019. In Column (4) of Table 4, GFP coefficient remains significantly negative, providing additional evidence of the model's robustness.

5.4.3 Controlling for other policy interventions

To address potential confounding from other environmental initiatives, the Low-Carbon City Pilot Policy and Key Air Pollution Control Zone Policy are introduced as additional controls. As reported in Columns (5) and (6) of Table 4, GFP coefficient remains significantly negative, underscoring the robustness of GFP effect on PCR.

5.4.4 Replacing the dependent variable

To further examine whether the baseline regression results are affected by the multiplicative construction of the original PCR indicator, following Bibo et al. (2024), this study uses the coupling coordination degree between environmental pollution and carbon emissions as an alternative measure of PCR. It should be noted that this coupling coordination degree is a positive indicator. The results are reported in Columns (7) of Table 4. The coefficient of the GFP is significantly positive, indicating that the policy significantly improves the coupling coordination degree between pollution reduction and carbon reduction. This suggests that the GFP not only affects the original PCR indicator, but also promotes the coordinated improvement of pollution reduction and carbon emission reduction. Therefore, the main conclusion is not driven by the multiplicative construction of the original PCR indicator and is robust.

Table 4
Robustness test results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variable	Advancing the policy implementation time	1:1 Nearest neighbor matching	Kernel matching	Shortened time window	Excluding the Low-Carbon City Pilot Policy	Excluding the key Air Pollution Control Zone Policy	Replacement of the dependent variable
did	-0.229	-0.544***	-0.542***	-0.371***	-0.462***	-0.467***	0.018**
	(0.160)	(0.157)	(0.157)	(0.141)	(0.127)	(0.127)	(0.007)
Constant	-3.865***	-2.259	-2.244	0.051	-4.568***	-4.340***	1.183***
	(1.277)	(1.667)	(1.666)	(2.024)	(1.279)	(1.279)	(0.072)
Control	√	√	√	√	√	√	√
City FE	√	√	√	√	√	√	√
Year FE	√	√	√	√	√	√	√
N	4368	2973	2977	2457	4368	4368	4368
R^2	0.321	0.345	0.346	0.399	0.327	0.324	0.808

5.5. Heterogeneity analysis

5.5.1. Regional heterogeneity

Based on the National Bureau of Statistics' regional classification, the sample is divided into eastern, central, and western cities, and heterogeneity regressions are conducted accordingly. Columns (1)–(3) of Table 5 show significantly negative GFP coefficients in the eastern and western regions, whereas the central-region coefficient is insignificant. Thus, GFP markedly enhances PCR in the eastern and western regions but shows no discernible effect in the central region.

5.5.2. Industrial base heterogeneity

Using the classification provided in the *National Plan for the Adjustment and Transformation of Old Industrial Bases (2013–2022)*, cities are grouped into old and non-old industrial base cities. Columns (4) and (5) of Table 5 show that GFP has a significantly negative effect on PCR in old industrial base cities, while the effect in non-old industrial base cities is statistically insignificant. This indicates that the policy's influence has not yet fully emerged in non-old industrial base cities in the short run.

5.5.3. Resource endowment heterogeneity

Following *the National Sustainable Development Plan for Resource-Based Cities (2013–2020)*, cities are classified as resource-based or non-resource-based, and heterogeneity regressions are conducted accordingly. The estimates in Columns (6) and (7) of Table 5 indicate significant GFP effects for both groups (–0.659 at the 1% level for resource-based cities; –0.320 at the 10% level for non-resource-based cities). This demonstrates that GFP enhances pollution–carbon coordination in all cities, with a markedly stronger impact in resource-based cities.

Table 5
Results of heterogeneity analysis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Regional heterogeneity			Industrial base heterogeneity		Resource endowment heterogeneity	
Variable	East	Centra	West	Old industrial base cities	Non-old industrial base cities	Resource-based cities	Non-resource-based cities
did	-0.519***	-0.120	-0.680***	-0.567***	-0.260	-0.659***	-0.320*
	(0.189)	(0.224)	(0.242)	(0.200)	(0.170)	(0.202)	(0.164)
Constant	-14.313***	-10.622***	5.032*	-5.712**	-3.597**	-1.907	-4.966***
	(2.138)	(2.275)	(2.756)	(2.332)	(1.539)	(1.969)	(1.705)
Control	√	√	√	√	√	√	√
City FE	√	√	√	√	√	√	√
Year FE	√	√	√	√	√	√	√
N	1552	1552	1264	1408	2960	1712	2656
R^2	0.420	0.480	0.178	0.267	0.373	0.353	0.312

5.6. *Mediation effect test*

5.6.1. GI

As shown in Columns (1) and (2) of Table 6, GFP exerts a significantly positive effect on the quantity of GI, indicating a strong policy-driven expansion of green patent applications. However, its effect on GI quality is positive but insignificant, implying limited incentives for higher-quality innovation. This pattern reveals a quantity-driven bias in the current GFP design, suggesting that GFP enhances PCR primarily through increases in the quantity, not the quality, of GI.

From the perspective of transmission mechanisms, although green finance policies have not significantly improved the quality of green innovation, they have indirectly promoted pollution and carbon reduction by increasing the quantity of green innovation (Acemoglu et al., 2012). On the one hand, the increase in green patent applications reflects greater corporate attention to green technologies and a stronger willingness to develop green projects, which helps promote the implementation and diffusion of energy-saving and emission-reduction projects (Mo et al., 2023); on the other hand, the expansion in the quantity of green innovation can accumulate green technological reserves that may be transformed into effective supplies for environmental governance and climate change mitigation once policy screening mechanisms are improved (Yuan et al., 2025).

5.6.2. INS

As shown in Columns (3) and (4) of Table 6, GFP has a significantly negative effect on INS upgrading, indicating that the policy has not yet accelerated the shift toward higher value-added sectors. This suggests that the INS upgrading channel works against the total effect and therefore constitutes a masking effect. Specifically, rather than immediately promoting structural upgrading, GFP may initially facilitate the green transformation of traditional industries, thereby partially offsetting its overall reduction effect on PCR. Nevertheless, the total effect of GFP on PCR remains significantly negative, implying that the direct effect and other transmission channels outweigh this offsetting channel and jointly lead to a net reduction in the PCR. By contrast, its effect on INS rationalization is positive but insignificant, suggesting that GFP has not yet substantially improved internal industrial coordination or resource allocation efficiency.

There are three main reasons for this result. First, during the initial stage of GFRIPZ policy, the focus was placed on green credit, project identification, and information disclosure, with policy objectives primarily aimed at improving the environmental compliance and pollution control capacity of traditional industries rather than advancing INS upgrading. This weakened the policy’s effectiveness in directing capital toward emerging industries (Aghion et al., 2016). Second, GF tends to favor high-tech green industries, which are typically high-risk and long-term, conflicting with the financial system’s preference for risk control and short-term returns. As a result, policy incentives have largely facilitated the “green repair” of traditional industries rather than their green substitution (Pástor et al., 2021). Third, improvements in resource allocation efficiency within industries depend more on government coordination and regional division of labor, while GFP lacks the capacity to directly address structural frictions and factor misallocations, thereby limiting their ability to fully exert industrial structural transmission effects.

5.6.3. ECCR

Columns (5) and (6) of Table 6 present the mechanism analysis based on ECCR. The regression results reveal that GFP significantly reduces energy consumption intensity and significantly increases green energy efficiency. This suggests that GFP facilitates PCR by improving energy-use efficiency and curbing overall energy consumption intensity.

This pattern may arise because GFP, as a key lever of green development, functions as an institution-based incentive and discipline mechanism that redirects financial resources from pollution-intensive sectors to energy-saving and emission-reduction industries through green project eligibility criteria, differentiated regulatory guidance, and mandatory environmental disclosure requirements (Chen et al., 2018). Under this institutional framework, the implementation of GFP by local governments in pilot cities raises financing barriers for high-pollution, high-energy-consuming, and overcapacity projects and tightens the assessment of firms' energy-use structure and emission intensity, thereby forcing firms to adopt energy-saving technological upgrades and improve their energy mix. Moreover, GFP tend to form a coordinated mechanism with institutional instruments such as dual control of energy consumption and green performance evaluation, thereby reinforcing accountability for energy-use responsibility in urban governance. In pilot cities in particular, GFP encourage financial institutions to closely associate credit allocation with firms' environmental performance, making energy-use efficiency an important condition for market-based financing; as a result, GFP significantly contribute to PCR through ECCR.

Table 6
Mechanism test results

	(1)	(2)	(3)	(4)	(5)	(6)
	GI		INS		ECCR	
Variable	Quantity	Quality	Upgrading	Rationalization	Energy consumption intensity	Green energy efficiency
did	0.162***	0.021	-0.084**	0.004	-0.016**	0.031**
	(0.042)	(0.072)	(0.041)	(0.018)	(0.007)	(0.015)
Constant	-2.891***	7.365***	7.139***	2.522***	0.842***	-0.474***
	(0.426)	(0.728)	(0.417)	(0.184)	(0.075)	(0.150)
Control	√	√	√	√	√	√
City FE	√	√	√	√	√	√
Year FE	√	√	√	√	√	√
N	4368	4368	4368	4368	4368	4368
R^2	0.725	0.187	0.622	0.111	0.277	0.220

5.7. Spatial effect test

5.7.1. Spatial correlation test

(1) To determine the necessity of spatial modelling, the global Moran's I statistic was calculated to test for spatial autocorrelation in PCR. Considering the physical diffusion characteristics and spatial continuity of pollutants and carbon emissions, this study adopts a geographical distance matrix, with the specific calculation procedure following (Mi et al., 2025). As shown in Table 7, Moran's I is significantly positive in each year, confirming the presence of spatial dependence. Therefore, it is necessary to employ a spatial

econometric model.

Table 7
Results of the global Moran's I test for PCR index

Year	Moran's i	Z-value	Year	Moran's i	Z-value
2008	0.053***	10.737	2016	0.070***	13.882
2009	0.049***	9.912	2017	0.057***	11.490
2010	0.048***	9.789	2018	0.056***	11.205
2011	0.057***	11.425	2019	0.053***	10.642
2012	0.064***	12.895	2020	0.084***	16.588
2013	0.067***	13.478	2021	0.046***	9.352
2014	0.072***	14.264	2022	0.042***	8.640
2015	0.074***	14.781	2023	0.035***	7.226

5.7.2. Selection of spatial econometric models

(2) Model selection. Based on the LM, LR, Wald, and Hausman test results in Table 8, the two-way fixed SDM emerges as the preferred specification for the empirical analysis.

Table 8
Results of the applicability test for the spatial econometric model

Spatial econometric model test		Statistic	P-value
LM test	Moran's I-error	89.538	0.000
	LM-error	7242.723	0.000
	Robust-LM-error	4632.003	0.000
	LM-lag	2737.973	0.000
	Robust LM-lag	127.253	0.000
LR test	LR-SDM/SEM	48.600	0.000
	Wald-SDM/SAR	62.240	0.000
Wald test	Wald-SDM/SEM	46.780	0.000
	Wald-SDM/SAR	62.820	0.000
Hausman test (Fixed/Random)		17.090	0.029
Both/ind test	LR-both/ind	27.040	0.028
	LR-both/time	5068.270	0.000

5.7.3. Analysis of regression results from the spatial Durbin model

In light of the model selection tests, the empirical analysis proceeds with a two-way fixed-effects SDM. The results in Table 9 show that the estimated coefficient of GFP is significantly negative at the 1% level, indicating that GFP implementation effectively promotes PCR after spatial relationships are accounted for. However, the indirect effect is significantly positive, implying an adverse impact on pollution and carbon emissions reduction in neighboring cities. This may be because, on the one hand, policy implementation attracts green financial resources, talent, and technological factors to pilot cities, thereby crowding out resources in surrounding areas and generating a "central siphon effect"; on the other hand, some highly polluting and carbon-intensive firms may relocate to neighboring cities to avoid policy constraints in the pilot areas, resulting in a "pollution haven" effect. Furthermore, the spatial autoregressive coefficients (ρ) in the SDM and spatial autoregressive model (SAR), as well as the spatial error coefficient (λ) in the spatial error model (SEM), are all significantly positive, suggesting that GFP has significant spatial spillover effects on PCR.

Table 9
Spatial econometric regression results

	(1)	(2)	(3)
Variable	SAR	SEM	SDM
did	-0.454***	-0.546***	-0.550***
	(0.122)	(0.121)	(0.121)
W×			
dp			11.239***
			(2.220)
Control	√	√	√
City FE	√	√	√
Year FE	√	√	√
ρ	0.916***		0.666***
	(0.017)		(0.071)
λ		0.929***	
		(0.011)	
σ^2	0.446***	0.434***	0.432***
	(0.010)	(0.009)	(0.009)
N	4368	4368	4368
R^2	0.008	0.263	0.191

6. Further analysis: spatial boundary of the spillover effects of GFP on PCR

Following the first law of economic geography, spatial interactions decline as distance grows. To test whether the spillover effects of GFP on PCR follow this distance-decay rule, this study applies the approach of Zhou and Tang (2022) by imposing varying distance thresholds. For any pair of cities, if the geographical distance exceeds the threshold, the value $1/d_{ij}$ is assigned; otherwise, the entry is set to 0, as defined in the equation below.

$$Thre_{ij} = \begin{cases} 1/d_{ij}, if \ \ 1/d_{ij} > d_t \\ 0, \quad if \ \ 1/d_{ij} < d_t \end{cases} \tag{6}$$

In Equation (6), represents the distance threshold. The initial value of is set to 0 and gradually increased in 100-kilometer increments until reaching 700 kilometers. Considering that when the threshold exceeds 700 kilometers, the impact of GFP on PCR becomes increasingly affected by provincial boundaries, and that excessive thresholds introduce noise due to outliers in the spatial spillover coefficient, only results within 700 kilometers are retained. Fig. 4 presents the spatial effects of GFP under different thresholds, showing that their impact on neighboring cities' pollution and carbon reduction is mainly concentrated within 300 kilometers, beyond which the spatial effect gradually diminishes. This finding suggests that the spatial effect of GFP on PCR not only exhibits a "neighboring spillover" pattern but also follows a "distance decay" law.

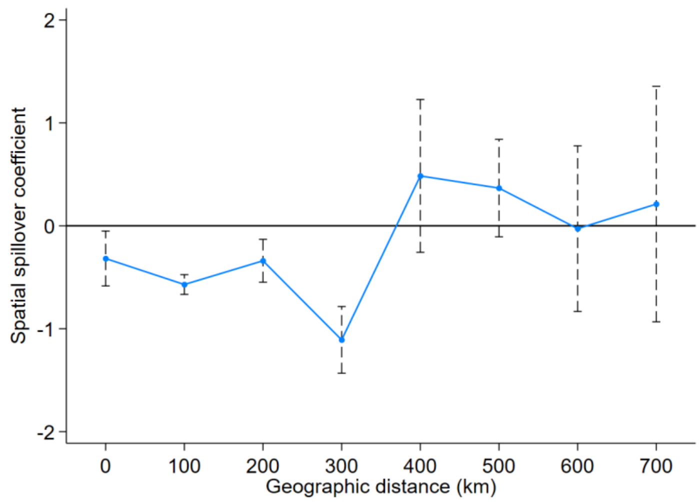

Fig. 4. Variation of the spatial spillover coefficient of GFP with geographic distance.

7. Conclusions and discussion

7.1. Conclusions

This study first examines the impact and spatial effects of GFP on PCR, and then conducts an empirical analysis based on panel data from 273 Chinese cities spanning the period from 2008 to 2023. The main findings are as follows: (1) GFP significantly promotes PCR, with the findings remaining robust to multiple robustness checks. The effect is especially strong in eastern and western China and in cities characterized as old industrial base or resource-based. (2) GFP facilitates PCR by increasing quantity of GI, reducing energy consumption intensity, and improving green energy efficiency; however, at the INS, INS upgrading exhibits a short-term masking effect, and its emission reduction potential has not yet been fully realized. (3) GFP exerts significant spatial spillover effects: they enhance PCR locally, but have negative spillover effects on neighboring cities, with these effects showing a characteristic of “neighboring spillover and distance decay.” Overall, the findings enrich the understanding of the transmission logic and spatial boundaries of financial policies in environmental governance, providing empirical evidence and policy insights for GF practices of developing economies.

7.2. Discussion

7.2.1. In terms of direct effects

GFP has significantly promoted PCR. This finding aligns with the OECD (2017) conclusion that “GF serves as a bridge between economic growth and environmental improvement,” and resonates with the European Green Deal (2019), which advocates for a “financial system-driven structural emission reduction” pathway. However, unlike the Western model, China’s GF framework is characterized by incremental institutional innovation centered on pilot zones, forming a policy synergy through a tripartite structure of government leadership, financial institution participation, and market mechanism embedding. This institutional design helps overcome the constraints of an underdeveloped market-based GF system and provides a practical model for developing economies to achieve green transition under institutional incompleteness. Furthermore, differing from the World Bank (2021) view that "financial intervention should be market-driven," China's pilot zones initially adopted a hybrid model combining regulation and guidance, establishing a system of binding incentives through green credit guidelines, green bond policies, and environmental information disclosure mechanisms. The empirical evidence demonstrates that this policy mix significantly enhances PCR performance, indicating that a government–market collaborative GF system yields higher implementation efficiency in the context of developing economies.

7.2.2. In terms of mediating effect

GI dimension, GFP significantly enhances the quantity of GI, but their effect on innovation quality remains insignificant. This result suggests that, in the short term, policy incentives tend to encourage firms to respond to policy evaluations through an increase in the number of patent applications, whereas high-quality and breakthrough green technologies require sustained financial support and long-term knowledge accumulation. Unlike the OECD (2023) findings for developed countries, China faces a "financing–technology dual constraint" in innovation quality, underscoring the need to further improve innovation-oriented financial mechanisms within its GF system.

INS dimension, GFP exerts a masking effect on the upgrading of INS, while its impact on structural rationalization is insignificant. This indicates that, in the early stages, policies primarily promote the "green rehabilitation" of traditional industries through green credit and risk management mechanisms rather than facilitating the "green substitution" of emerging sectors. This finding contrasts with the EU experience, where GF predominantly supports innovation investments in high-tech industries, while China remains in a transition phase dominated by emission-reduction-oriented industrial retrofitting. Going forward, efforts should focus on greening the capital market, fostering financial product innovation, and aligning with industrial policies to channel capital toward high–value-added sectors and prevent delays in INS upgrading.

ECCR dimension, GFP significantly reduce energy consumption intensity and enhance green energy efficiency, indicating that such policies improve energy utilization efficiency through financing structure optimization and technological upgrading. This finding is consistent with the World Bank (2021) conclusion that "green credit promotes energy efficiency improvement," and it further confirms the central mediating role of the energy mechanism between GF and environmental performance. Hence, GF in China's environmental governance has entered a transitional phase, rom mere financial support to structural optimization.

7.2.3. In terms of spatial effects

GFP exhibits significant spatial spillover effects and a clear distance decay pattern, with their influence primarily concentrated within 300 kilometers. This finding reveals the geographical boundary effect of financial policy diffusion: on the one hand, close economic linkages, information sharing, and capital flows among geographically proximate cities accelerate the transmission of GF effects, forming a “positive synergy” mechanism; on the other hand, the relocation of high-emission enterprises to non-pilot areas may give rise to a “pollution haven” effect in neighboring regions. The coexistence of these “positive spillover” and “negative migration” dynamics underscores the importance of regional coordination, implying that the effectiveness of GFP depends not only on local implementation intensity but also on cross-regional institutional alignment and spatial governance mechanisms. Compared with the EU’s “Cross-Border Green Finance Mutual Recognition Mechanism,” China’s regional GF policies still face institutional barriers and administrative fragmentation, limiting the spatial transmission of policy spillovers. Therefore, it is essential to establish a tiered management model comprising core, buffer, and diffusion zones, and to strengthen interregional financial collaboration and information-sharing mechanisms to ensure the balanced diffusion of policy effects.

8. Policy implications and limitations

To enhance the regional coordination and structural optimization mechanisms of GFP, efforts should be made to ensure that GF plays a more balanced and efficient role in promoting PCR across multi-level urban systems. First, strengthen policy differentiation and performance orientation by integrating pollution and carbon reduction objectives into financial supervision and local government performance evaluation, thereby increasing GF support in central regions, non-old industrial bases, and non-resource-based cities. Second, optimize incentive structures to shift GFP from quantity-oriented innovation toward quality-oriented innovation, enhancing long-term financing for energy-efficient projects and core green technologies to promote INS upgrading and energy efficiency improvements. Third, establish a cross-regional coordination mechanism for GF and pollution transfer prevention by unifying project classification and environmental information disclosure standards, mitigating resource siphoning and emission relocation, and fostering a spatially coordinated emission reduction pattern among regions.

This study has several limitations. First, although this study employs a two-way fixed effects model, parallel trend tests, PSM-DID, placebo tests and a series of robustness checks to mitigate policy selection bias and endogeneity concerns as far as possible, it cannot fully rule out the potential influence of unobservable time-varying factors. Second, due to the limited availability of city-level energy consumption data, this study uses electricity consumption per unit of GDP as a proxy for energy intensity. This indicator mainly captures electricity use intensity and cannot be fully equated with overall energy intensity, which includes coal, oil, natural gas and other forms of energy consumption. Third, some city-level carbon emissions and energy-related indicators are estimated from statistical data or databases, which may introduce measurement errors. Future research could further identify the causal effects of GFP on PCR by using richer micro-level data, stronger exogenous shocks and more accurate city-level data on energy consumption and carbon emissions.

Declarations

1.Availability of Data and Materials

The datasets generated and analysed during the current study, including the processed city-level panel data, variable definitions, and empirical codes, are available from the corresponding author upon reasonable request.

2.Competing Interests

The authors declare that they have no competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. This disclosure covers the last three years of conducting and preparing the research, and any older interests that could reasonably be perceived as influencing the work.

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