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Shubo Yang

Guizhou University of Finance and Economics

Chao Li

Guizhou University of Finance and Economics

Ting Xu

Nanjing University of Finance and Economics

Muhammad Adnan Bashir

adnanbashir2034@gmail.com

Guangdong University of Foreign Studies

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Achieving a green transition: how local government targets reduce pollution and emissions: a quasi-natural experiment from chinese cities

Shubo Yang¹, Chao Li¹, Ting Xu², Muhammad Adnan Bashir³

¹School of Applied Economics,
Guizhou University of Finance and Economics, Guiyang, 520025, China.

²Institute of Food and Strategic Reserves,
Nanjing University of Finance and Economics, Nanjing 210003, China.

³Guangdong Institute for International Strategies,
Guangdong University of Foreign Studies, Guangzhou, Guangdong, P.R. China.

Corresponding Author's Name: **Muhammad Adnan Bashir**

Corresponding Author's Email: adnanbashir2034@gmail.com

Abstract: This study examines whether and how local government environmental targets contribute to achieving synergistic reductions in pollution and carbon emissions, a key challenge for sustainable development in emerging economies. Using a panel dataset of 213 prefecture-level cities in China from 2011 to 2021, we exploit the staggered introduction of environmental targets as a quasi-natural experiment and employ a time-varying difference-in-differences approach combined with spatial econometric analysis. The results show that the implementation of binding environmental targets significantly enhances the joint reduction of air pollutants and carbon emissions, supporting a “co-benefit” pathway toward green transition. Mechanism analysis reveals that these effects operate through four primary channels: technological innovation, industrial structure upgrading, green finance expansion, and improvements in energy efficiency. Furthermore, we identify positive spatial spillover effects, indicating that strengthened environmental governance in one city can generate broader regional sustainability benefits. Heterogeneity analysis demonstrates that the effectiveness of environmental targets varies across city characteristics, with stronger impacts observed in non-resource-based, highly marketized, and small- to medium-sized cities. These findings highlight the importance of institutional capacity and economic structure in shaping environmental outcomes. This study contributes to the literature by providing new empirical evidence on the role of decentralized environmental governance in promoting coordinated pollution and carbon reduction. More importantly, it offers policy-relevant insights for developing countries seeking to balance economic growth with environmental sustainability, emphasizing the need for well-designed target systems and regional coordination mechanisms to achieve long-term sustainable development goals.

Keywords: Environmental Targets; Pollution Reduction; Carbon Emissions; Technological Innovation; Local Government; Spatial Spillover

Jel Codes: Q58, Q53, H23, C33, O44

1.Introduction

In the wake of escalating global environmental challenges, assisting the national governments, the local governments are assuming a pivotal role in curbing pollution and mitigating carbon emissions (Xiao et al.,2018; Chen et al.,2024). Embedded as a cornerstone of sustainable development, environmental conservation has emerged as an imperative obligation and trial for governments across all tiers. The objective of environmental safeguarding transcends mere moral obligation, standing as a vital agenda for local administrations to enhance citizens' quality of life and propel sustainable economic progress. Nonetheless, crafting efficacious environmental policies to attain the twin goals of pollution abatement and carbon mitigation remains a formidable task.

Whether local governments are effectively achieving their environmental goals and the effective constraints these goals place on their actions are important for both regional pollution and carbon abatement. Despite the extensive literature on environmental policy and regulation, these critical issues have not garnered adequate attention. This paper significantly advances the existing literature by examining how environmental objectives set at the local level, as outlined in municipal government work reports, influence emission outcomes through both direct and spillover effects. Departing from the predominant focus on regulatory outcomes or central mandates, this research utilizes these local targets as quasi-natural experiments and introduces an innovative composite metric, termed the Pollution and Carbon Reduction Effect, to evaluate synergistic impacts on pollution and carbon reduction. On the one hand, local governments have limited resources and economic growth and eco-friendliness are often at odds in the short term, leading governments to potentially skew their policy preferences and exhibit strategic behavior (Mohammed et al.,2024). On the other hand, some local governments have adopted deterministic and precisely quantified environmental targets, pressured themselves to impose stricter environmental regulations, promoted green innovation and industrial transformation, and even altered the spatial distribution of polluting industries through "pollution shelters" in order to improve local environmental performance (Ya et al.,2024).

From existing research, numerous scholars have concentrated on the influencing factors of local government target adjustments and the synergistic effects of pollution and carbon reduction. The former is primarily analyzed from the standpoint of local government behavior and the perspective of environmental target management. Some studies suggest that higher-level governments assess local officials based on the achievement of targets by lower-level governments (Zhou et al., 2013). Consequently, local governments may exhibit a series of behavioral responses to meet these goals. For instance, to fulfill economic growth targets, local governments may incentivize local enterprises, particularly state-owned enterprises, to expand investments and reduce tax burdens, and may even resort to data falsification (Xu et al.,2020; Lu et al.,2024). Furthermore, some studies have analyzed the impact of environmental regulation on various aspects such as industrial structure (Song et al., 2021), production efficiency (Lv et al., 2023), foreign investment (Yin et al.,2024), and green innovation (Zhang et al., 2022), as well as pollution emissions, all from the perspective of government environmental target management (Zhang & Hao, 2020).

The subsequent studies have primarily focused on several key aspects, including the unidirectional synergistic benefits associated with "carbon and pollution" or "pollution and carbon", the bidirectional synergistic advantages stemming from integrated abatement measures, and the evaluation of the synergistic impacts on health and costs (Zhao et al., 2019; Hui et al., 2022; Wang

et al., 2024; Xiao et al., 2024). For instance, Xiao et al. (2024) elucidated a notable U-shaped correlation between pollution abatement pressure and CO₂ emissions. Below a critical threshold of pollution abatement pressure, a reduction in CO₂ emissions is observed. However, beyond this pivotal point, CO₂ emissions exhibit an upward trend. Moreover, it has been observed that various policies and measures targeting air pollutants have demonstrated a positive synergistic effect on emission reductions (Tollefsen et al., 2009; Dong et al., 2019). Cai et al. (2016) posited that as local environmental assessments are fortified, local governments, driven by the imperative to meet environmental targets while sustaining economic growth, may opt to relocate polluting industries to border regions. This strategic maneuver exacerbates the localized issue of border pollution. Zhao et al. (2019) found that achieving the 80% GHG reduction target would result in significant air quality and health synergistic benefits by using an integrated approach combining energy and emissions technology modeling, high-resolution chemical transport simulations, and health impact assessments.

Overall, while there is extensive research exploring the effects of environmental targets and emissions, studies analyzing the synergistic effects of pollution reduction and carbon reduction from the perspective of environmental targets are relatively rare. Only a few scholars have empirically demonstrated the positive effects of the target responsibility system and the establishment of environmental targets on air quality improvement. For instance, Zhang and Wu (2018) conducted a study based on cross-sectional data from 267 prefecture-level cities in China, revealing that for every 1% increase in environmental targets, the annual average urban PM_{2.5} concentration decreased by 0.5283 $\mu\text{g}/\text{m}^3$. However, the synergistic effects of environmental policies have faced skepticism from some scholars. Sinn (2008) introduced the "green paradox" as a counter-argument, suggesting that ambitious government policies to reduce environmental emissions may sometimes have counterproductive effects on greenhouse gas (GHG) emissions. This is attributed to the dynamic supply-side response of producers, which anticipates future policy changes and accelerates fossil energy extraction and consumption. The "green paradox" challenges the notion that ambitious environmental policies always lead to emission reductions and has been supported by evidence in several studies (Van & Withagen, 2015).

Therefore, this paper utilizes the environmental targets set by local governments as a quasi-natural experiment of exogenous shocks, with the aim of examining the impact of the government's reinforced environmental targets on the local effects of pollution and carbon reduction. The implementation of environmental targets has heightened the importance of the government's target system, and in some cases, has even introduced the "one-vote veto system" for environmental issues. Additionally, local governments possess strong incentives to meet their targets (Xu et al., 2011). Faced with the pressure of strengthened environmental targets, local governments are inclined to proactively enhance supervision and improve the environment, thereby successfully establishing an effective constraint mechanism for local governments to safeguard the environment.

Compared with existing studies, this paper makes several marginal contributions. First, it offers a unique research perspective within the field of environmental regulation. While much of the existing literature primarily focuses on the governance effects of environmental regulation or on the policies themselves, this paper shifts the focus towards examining the disparities in the effects of local governments' environmental regulation. Second, this paper introduces an innovative research methodology to manually compile municipal government work reports from across China for multiple years. By employing a combination of text mining, contextual screening, and lexical

comparison, it constructs a comprehensive policy variable for local government environmental objectives. This methodology not only provides a more detailed and nuanced representation of government intentions but also enhances the robustness of the findings by incorporating textual analysis to identify subtle shifts in policy rhetoric and goals over time. Third, this study investigates the impact of the environmental target responsibility system on government goal-setting processes. By examining how these target-setting processes reflect broader socio-economic planning and development goals, this paper contributes to the growing literature on local government behavior, especially in the context of multi-objective trade-offs between economic growth, environmental sustainability, and social welfare. In doing so, it offers new insights into the complexity of government decision-making when balancing multiple competing objectives, enriching the theoretical understanding of government action in the realm of environmental policy.

The remainder of the paper is structured as follows: the second section presents the theoretical analysis and hypotheses, and the third section describes the research design of the paper. The fourth section demonstrates the analysis of the results of this paper. The fifth section is the extended analysis. The sixth section is the conclusion and policy implications. Figure 1 presents the framework structure of this paper.

2. Theoretical analysis and research hypotheses

2.1 The impact of environmental targets on pollution and carbon reduction

This study builds on classical environmental economics theories to frame the impact of local government environmental targets. The analysis integrates insights from Porter's Hypothesis (Porter, 1991; Porter & van der Linde, 1995), the Environmental Kuznets Curve (Grossman & Krueger, 1995), and jurisdictional competition theory (Tiebout, 1956; Fredriksson & Millimet, 2002).

In the model, local governments announce annual quantitative environmental targets in their Government Work Reports. These targets are treated as hard constraints that enter both the enterprise profit-maximization problem and the local government's objective function under China's cadre evaluation system. Following the evolution of environmental quality is governed by:

$$Q_{t+1} = hQ_t + (1 - h)\bar{Q} - \omega(1 - EP_t)M_t \quad (1)$$

Where Q_t is environment quality, $h \in (0,1)$ is the natural self-purification rate, ω is the emission coefficient per unit of energy, $EP_t \in (0,1)$ is the abatement effort, and M_t is energy consumption. Local environmental targets effectively impose a lower bound EP_t or an upper bound on emission, forcing firms and local governments to internalize the pollution externality.

In the enterprise sector, a nested constant-elasticity-of-substitution production function augmented with energy and abatement technology is adopted (Xiao et al, 2018):

$$Y_t = A_t [\alpha_K K_t^\rho + \alpha_L (L_t)^\rho + \alpha_M (\eta_t^M M_t (1 - EP_t)^\phi)^\rho]^{1/\rho} \quad (2)$$

Where higher mandated EP_t raises the effective cost of energy, inducing substitution toward cleaner inputs and innovation. The representative local government maximizes a weighted objective of GDP growth and environmental performance, generating a top-down pressure transmission mechanism. Under these conditions, stricter local environmental targets unambiguously reduce equilibrium pollution stock and carbon emissions in the long run. Consequently, we propose:

H1: Binding local environmental targets significantly reduce regional pollution and carbon emissions

2.2 Mechanism analysis

Drawing on the decomposition framework of Brock and Taylor (2005), environmental targets affect emissions through three primary channels: technological effect, structural effect, and scale effect.

2.2.1 Technological effect

Environmental targets increase the shadow price of emissions, triggering both “end-of-pipe” treatment and “clean technology” innovation. Firms face an optimized abatement effort:

$$EP_t = \operatorname{argmax} \pi_t = p_t Y_t - \text{costs} - \frac{\gamma}{2} (EP_t)^2 Y_t - \tau^e \omega (1 - EP_t) M_t \quad (3)$$

When a binding target raises the effective emission tax equivalent τ^e or directly mandates $EP_t > EP^{\text{voluntary}}$, firms increase R&D expenditure and patenting in green technologies (Porter & van derLinde, 1995; Calel & Dechezleprêtre, 2016). The innovation compensation effect partially or fully offsets compliance costs, especially in regions distant from the technological frontier (Alpay et al., 2002; Yuan & Zhang, 2020). Consequently, we propose the following hypothesis (H2a):

H2a: Environmental targets mitigate pollution emissions through the enhancement of technological innovation.

2.2.2 Structural effect

Environmental objectives can promote industrial greening through structural adjustments that help reduce pollution emissions. First, environmental regulations are increasingly leveraging digital technology at various stages of production, facilitating the digital transformation of polluting industries and encouraging their expansion into diverse sectors, which collectively advances industrial greening. Additionally, green credit policies are improving capital allocation efficiency to stimulate the growth of environmentally friendly industries (Li & Chen, 2022). Such policies also broaden financing options, which eases the development of green technologies, further advancing environmental quality and green technology uptake within enterprises (Soundarrajan & Vivek, 2016). Industrial sustainability initiatives also play a significant role in achieving pollution reduction and carbon emission targets. For instance, environmental protection taxes incentivize firms to adopt green technologies, increase energy efficiency, and reduce emissions at the production chain's endpoint (Kemp & Pontoglio, 2011). While green credit policies promote sustainable industries, they may face resistance from capital-intensive firms reliant on traditional financing, necessitating complementary enforcement mechanisms (Li & Chen, 2022). Based on this rationale, the current study proposes the following hypothesis (H2b):

H2b: Local environmental targets reduce pollution and carbon emissions by promoting the greening of industrial structure.

2.2.3 Scale effect

Environmental objectives play a crucial role in curbing energy consumption and reducing pollution emissions through the scale effect. Economic growth, while beneficial, typically drives expanded economic activities, leading to increased demands for resources and energy. This expansion intensifies pollution emissions and amplifies environmental impacts

From a governmental perspective, local governments, balancing environmental constraints with economic growth targets, often strengthen environmental regulation to create a “forcing effect” (Tian & Feng, 2022). This approach encourages the phasing out of industries that are high in pollution and energy consumption, simultaneously promoting the development of new industries and business models aligned with sustainable economic growth. Heightened regulation compels businesses to adopt cleaner energy sources and pursue technological innovations in energy usage,

leading to improved energy efficiency, reduced energy consumption, and mitigation of pollution and ecological harm (Marconi, 2012). Alongside this, a growing awareness of environmental issues drives societal engagement in green practices, such as low-carbon travel, sustainable consumption, and energy-saving behaviors. Consequently, a green, low-carbon trend is emerging across society, reinforcing public commitment to environmental protection and deepening awareness of environmental rights (Cohen & Vandenberg, 2012). This comprehensive view supports the formulation of Hypothesis (H2c):

H2c: Local environmental targets reduce pollution and carbon emissions by lowering energy consumption and improving energy efficiency.

2.3 Spatial spillover effects

In a spatially interconnected economy, unilateral strengthening of environmental targets generates significant externalities. First, under China's promotion tournament, officials engage in strategic interaction: an increase in one prefecture's environmental stringency triggers mimetic or differentiated responses in neighboring jurisdictions (Chen, 2014; Liu et al, 2024). Second, air pollutants and CO₂ exhibit transboundary diffusion, creating a physical basis for spillover. Third, industrial relocation induced by strict regulation in one area raises emissions in neighboring lax regions ("pollution haven" effect) or, under coordinated central pressure, induces a synchronized upgrading ("race to the top"). Since the inclusion of environmental indicators in cadre performance evaluation after 2013, China has shifted from "bottom-up" to "top-down" competition, significantly strengthening positive spatial spillovers (Zhao & Wang, 2022; Guliyev, 2024).

H3: The implementation of stringent local environmental targets generates positive spatial spillover effects, reducing pollution and carbon emissions in neighboring cities.

3. Research design

3.1 Identification strategies

In this paper, we select the establishment of environmental targets by local governments as a quasi-natural experiment to evaluate their effectiveness in mitigating pollution and reducing carbon emissions. Owing to the asynchronous implementation of these environmental targets, we utilize a time-varying Difference-in-Differences (DID) approach to analyze and construct the baseline model.

$$PCRE_{it} = \alpha + \beta EG_{it} + \gamma X_{it} + \delta_i + \varphi_t + \varepsilon_{it} \quad (4)$$

In the above equation, i denotes the city and t represents the year. The dependent variable, $PCRE$, quantifies the urban pollution and carbon reduction effect observed in city i at year t . The core explanatory variable, EG , represents the environmental goals set by local governments and constitutes the primary focus of our analysis, examining its impact on urban environmental outcomes. X_{it} includes a series of control variables affecting $PCRE$. δ_i denotes the city fixed effect and φ_t denotes the time-fixed effect. ε_{it} is the error term.

Furthermore, to estimate the spatial spillover effects of environmental targets, this study constructs a Spatial Durbin Model (SDM). According to LeSage & Pace (2009), spatial econometric models should initially adopt the SDM to test the viability of alternative models. Building on the findings of Yang et al. (2023), this paper designates the local government environmental goals (EG) as the principal explanatory variable. A rigorous selection process for control variables has been undertaken to establish the following Spatial Durbin Model:

$$PCRE_{it} = \rho WPCRE_{it} + \beta EG_{it} + \lambda WEG_{it} + \eta X_{it} + \sigma WX_{it} + \delta_i + \varphi_t + \varepsilon_{it} \quad (5)$$

$$\varepsilon_{it} = \lambda W\varepsilon_{it} + \mu_{it} \quad (6)$$

In the above model, W represents the spatial weight matrix, ρ is the spatial regression coefficient for $PCRE$, and λ denotes the spatial autocorrelation coefficient of the error term. μ_{it} is the random disturbance term uncorrelated with $W\varepsilon_{it}$. The other variables are the same as in Model (1).

3.2 Variable selection

Explained variables: The Pollution and Carbon Reduction Effect (PCRE) is constructed to capture the synergistic reduction of carbon dioxide (CO₂) and atmospheric pollutants (PM_{2.5}, PM₁₀, NO_x, SO₂), reflecting the integrated nature of China's environmental targets (Dong et al., 2019). Unlike direct emissions or emissions intensity, PCRE accounts for year-over-year changes, enabling a dynamic assessment of policy impacts. The calculation method for the equivalent emission intensity of atmospheric pollutants references the study conducted by Zhang et al. (2018), and the formula is as follows:

$$Eq_{it} = (\alpha Q_{it,PM_{10}} + \beta Q_{it,PM_{2.5}} + \gamma Q_{it,SO_2} + \delta Q_{it,NO_x}) / GDP_{it} \quad (7)$$

Where $Q_{it,PM_{10}}$, $Q_{it,PM_{2.5}}$, Q_{it,SO_2} , and Q_{it,NO_x} represent the emissions of four typical atmospheric pollutants from city i in year t . According to the provisions of the "Environmental Protection Tax Law", the coefficients α , β , γ , and δ are set at 1/2.18, 1/2.18, 1/0.95, and 1/0.95 respectively. Since this study focuses on the effects of pollution reduction and carbon reduction, a negative sign is applied to these change rates, denoted as d_{it,CO_2} and $d_{it,Eeq}$. A positive value indicates a reduction trend, and vice versa. Considering that the values of d_{it,CO_2} and $d_{it,Eeq}$ can be both positive and negative, $PCRE$ (%) is constructed using the following formula:

$$PCRE_{it} = \sqrt{|d_{it,CO_2} * d_{it,Eeq}|} * \frac{d_{it,CO_2} + d_{it,Eeq}}{|d_{it,CO_2}| + |d_{it,Eeq}|} \quad (8)$$

In the foregoing equation, d_{it,CO_2} and $d_{it,Eeq}$ signify the inverse rates of change in annual emission intensities for two distinct emissions within prefecture-level city i in year t , respectively. Should d_{it,CO_2} and $d_{it,Eeq}$ exhibit congruent positive or negative values, the $PCRE$ is computed as the geometric mean of the two, signifying either a synergistic decrease or increase, respectively. Conversely, when d_{it,CO_2} and $d_{it,Eeq}$ diverge in sign—one positive, the other negative—the sign of the $PCRE$ is determined by their algebraic sum. This research defaults to employing logarithmic values of waste gas (specifically, sulfur dioxide emissions) and wastewater to quantify environmental pollution levels.

Explanatory variables: This research approach is inspired by Zhang and Wu (2018), captures the presence of explicit policy commitments. To ensure robustness, we explore a continuous measure of target intensity (e.g., percentage reduction goals) in Section 4.4, where available. Existing research predominantly focuses on environmental governance outcome indicators to measure regulatory intensity. Examples include the SO₂ treatment rate (Yang et al., 2016), wastewater compliance rate (Riva et al., 2020), and investments in pollution treatment (Ren et al., 2022). These studies underscore a robust causal link between the intensity of environmental governance and its outcomes, validating the use of outcome-based indicators as proxies for governance intensity. However, such indicators may not adequately capture the specific constraints that local government targets impose on environmental governance. To address this gap, the current study devises a novel approach by extracting and analyzing environmental governance-related expressions from the annual work reports issued by local governments.

In this study, the targets for energy conservation and emission reduction across each prefecture-level city are meticulously compiled from government work reports spanning from 2011 to 2021.

This data collection was performed manually, ensuring a thorough review and extraction of relevant information. By systematically analyzing the articulated goals within these reports, the paper aims to ascertain the extent to which stated objectives decode into environmental policy effectiveness and to assess their consequential impacts on environmental quality.

The primary data sources for local environmental targets in this study are threefold. First, the foundational data is derived from the texts of government work reports, this constitutes the core dataset for analyzing local government environmental targets. Second, as a significant supplement to these targets, additional reports are legally obtained through requests for public disclosure of government information, in accordance with relevant transparency regulations. Third, certain data points are acquired through the purchase of databases from specialized websites. If a report explicitly specifies numerical targets for pollution control—such as statements like "reduce energy consumption per unit of GDP by 4%", "decrease sulfur dioxide emissions by 3% or maintain total emissions below 0.88 million tonnes", or "lower chemical oxygen demand by 2% or cap it at 0.87 million tonnes"—the respective region is considered to have definitive environmental targets. Such regions are assigned a value of 1 in our dataset. Conversely, if no specific numerical targets are mentioned, a value of 0 is recorded. To cope with the potential endogeneity of the environmental target (Target), we used river network density as an instrumental variable, as it is highly correlated with the intensity of environmental regulation (higher density implies more monitoring sites) and exogenous to economic activity (Nunn & Qian, 2014).

Control Variables: In an effort to rigorously analyze the determinants of PCRE, this study incorporates a set of control variables informed by prior literature (Zefeng et al.,2018; Yang et al.,2024). These variables are carefully chosen to account for potential confounders that could influence the relationship between local government environmental governance target constraints and PCRE outcomes. The selected control variables include: **Industrial Structure (IS)**. Typically represented by the ratio of secondary industry output to total GDP. This metric is vital as regions with heightened industrial activities often encounter distinct challenges and opportunities in mitigating pollution and reducing carbon emissions. **Economic Development (ED)**. Commonly assessed by the Gross Domestic Product (GDP) per capita at the prefecture level. This measure reflects a region's economic capacity to enact and sustain environmental policies. **Population Density (PD)**. Defined as the number of inhabitants per square kilometer and taken in logarithms. Higher population densities can alter environmental dynamics, potentially impacting both pollution levels and the effectiveness of policy measures designed to curb them. **Level of Openness to the Outside World (LO)**. Frequently quantified by the percentage of Foreign Direct Investment (FDI) relative to GDP, where FDI is calculated based on the actual inflow of foreign capital, converted to RMB using the average middle exchange rate for the year. **Financial Development (FD)**. Measured by the proportion of financial institution deposits to GDP within each city. **Technological Input (TI)**. Evaluated by the expenditure on science relative to GDP for each city. **Consumption Behavior (CB)**. The environmental impact of local manufacturing processes is influenced by consumer habits, measured by the logarithm of total retail sales of consumer goods.

3.3 Data sources and descriptive statistics

This study utilizes panel data from 213 cities across China to evaluate the efficacy of local environmental objectives on pollution and carbon emission reduction. The data were sourced from government work reports available on the websites of each prefecture-level city, along with the China Urban Statistical Yearbook, the China Regional Economic Statistical Yearbook, the respective

provincial statistical yearbooks, and various public websites. To adjust for price variations over time, all monetary values were deflated using the provincial price indices, taking 2003 as the base year.

Notably, due to the presence of missing values in the municipal GDP data reported in the statistical yearbooks, this study utilizes raster GDP data, as estimated by Zhao et al. (2017), to construct a comprehensive economic dataset. The municipal GDP figures were derived through a process of regional summation, ensuring a more accurate and complete representation of economic activity across the studied cities. This approach addresses data gaps and enhances the reliability of our economic analysis. The foundational data for carbon emissions and air pollutant emissions were derived from the MEIC emission inventory database. Given that the latest data, the study period has been established as spanning from 2010 to 2023. For instances of missing data within the dataset, interpolation methods were employed to estimate missing values, ensuring the integrity and continuity of the analysis. Descriptive statistics for the primary variables are presented in Table 1.

4. Empirical analysis

4.1. Benchmark regression

The principal factors influencing the dependent variable in Equation (7); the outcomes of this process are presented in Table 2. We noted that environmental targets significantly contribute to reductions in pollution and carbon reduction; these findings remain robust across various fixed effects and control variables. Standard errors associated with these results are clustered at the municipal level.

As depicted in Column (8) of Table 2, environmental targets exert a negative impact on PCRE. Specifically, a 1% increment in urban environmental targets correlates with a reduction in PCRE by 0.871%. The results of this benchmark regression validate Hypothesis 1. This outcome may be ascribed to the enhanced motivation and more definitive guidance exhibited by local governments in the deployment of pertinent policies and strategies. This strategic distribution of resources and capital enhances the efficiency of environmental investments. Through these integrated actions, local governments can substantially bolster efforts in urban pollution control and carbon reduction, thus perpetually enhancing environmental quality.

4.2. Parallel trend test

We utilized event study methodology to scrutinize the dynamic effects and validate the parallel trend assumption underlying our DID model. To quantitatively test for pre-existing differences, we formally tested the joint hypothesis that all pre-treatment coefficients are equal to zero. The resulting F-test yielded a p-value of 0.342, allowing us to fail to reject the null hypothesis of no significant pre-trends.

As depicted in Figure 2, the coefficients prior to the implementation of environmental objectives exhibit relative stability and are predominantly non-significant over the five-year period, indicating no substantial disparities in PCRE between the treatment and control groups before the formal enactment. This observation suggests that, barring any collusion, the cities would have met the parallel trend criterion necessary for the DID analysis. Subsequently, a shift in trend is observable post-introduction of the environmental objectives, with the coefficients turning significantly negative.

4.3. Placebo test

If significant explanatory variables are omitted from the identification framework of the econometric model, this may lead to biased regression results. Following the approach of Yang et

al. (2024), we employ a placebo test using a random sampling method, a technique that has been widely applied in studies utilizing the DID methodology. The specific procedure is as follows: First, from a pool of 213 sample cities, a number equivalent to the actual number of cities targeted by environmental objectives in various years is randomly and non-repetitively selected to form the treatment group, with the remaining cities serving as the control group. Second, this randomly selected treatment group is aligned with the years of environmental policy implementation to create a fictitious policy variable, denoted as DID. Third, keeping other control variables constant, this variable DID is substituted into Model (1) for regression. As shown in Figure 3, the estimated coefficients of the variable DID are centered around zero and display significant differences from the baseline regression results, thereby validating the reliability of the initial regression conclusions derived earlier.

4.4. Robustness tests

4.4.1. Transforming explanatory variables

To further substantiate the reliability of our regression findings, we explore additional alternative indicators to measure the pressure exerted by environmental targets, conducting regression analyses accordingly. In column (1) of Table 3, we take "the ratio of the actual ammonia nitrogen emissions in the current year/the ammonia nitrogen emissions issued by the central government to the province in the current year" as the target pressure on the environment, while other control variables remain unchanged. The analysis reveals that the pressure from environmental targets is negatively correlated with the outcome of one of the regressions, with this result being statistically significant at the 1% level. The findings consistently indicate that regardless of the specific indicator used to quantify environmental target pressure, its impact on PCRE is invariably negative.

4.4.2. Transforming the explained variables

To validate the regression results from the previous section, we conducted a robustness analysis by substituting the explained variables. We employed logarithmic transformations of emissions data, specifically focusing on sulfur dioxide emissions and wastewater outputs, to quantify the level of environmental pollution. The outcomes of this robustness testing are documented in columns (2) and (3) of Table 3. The regression analysis demonstrates that the estimated coefficients remain significantly negative when the explained variables are replaced with sulfur dioxide emissions and wastewater, thereby reinforcing the reliability of the initial findings.

4.4.3. Heterogeneous treatment effects

When using time-varying DID models for estimation, it is important to consider that heterogeneous treatment effects may arise. Such as, variability can introduce biases into the estimates, potentially distorting the assessment of the policy's impact. To address this complexity, we draw on the methodological framework proposed by De and d'Haultfoeuille (2020), which enhances the precision of estimating treatment effects at specific times while accounting for their temporal variations.

This methodology encompasses several key components: First, it entails estimating treatment effects separately for each group and time point by segmenting the data based on when the treatment was administered. Second, it facilitates the estimation of treatment effects for individuals who commenced treatment at distinct times. Third, it involves adjusting for potential confounders by controlling for relevant covariates, which sharpens the accuracy of the estimated treatment effects. The findings presented in column (1) of Table 4 indicate that the estimated coefficients are significantly negative. This outcome suggests that the conclusions drawn from the initial benchmark

regression analysis remain robust, even after accounting for the issue of heterogeneous treatment effects.

4.4.4. Considering province-time interaction fixed effects

This study incorporates province-time interaction fixed effects into the baseline regression model to account for temporal variations across different provinces as cities within the same province often share similar policy environments. The results, displayed in column (2) of Table 4, affirm that the impact of environmental target on PCRE remains significantly negative at the 1% significance level, even after adjusting for the correlated effects of city characteristics within the same province. This finding substantiates the robustness of the original conclusions drawn from the study.

4.4.5. Removal of outlier impacts

Due to the potential for outliers to skew regression estimates, this study omits the year 2020 from the sample in the baseline regression. This adjustment is aimed at mitigating the impact of these anomalous data points. The specific regression results are presented in column (3) of Table 4. The findings indicate that even with the exclusion of such outliers, the overall conclusions of the study remain substantially unchanged, reinforcing the robustness of the initial results.

4.4.6. Exclude the impact of concurrent policy

This study checks policies potentially impacting PCRE from 2010 to 2020. Firstly, the comprehensive demonstration cities for energy-saving and emission reduction fiscal policies initiated in 2011 are included. We incorporate the energy-saving and emission-reduction fiscal policy dummy variable *Fiscal* in the baseline model to account for its potential effects on PCRE fluctuations. Second, the key control areas for special emission limits for air pollutants established in 2013 are considered. This analysis constructs the dummy variable *Pollutant* to capture the impact of this policy. Third, urban environmental legislative authority was formalized by the 2015 PRC Legislative Law. For this, the dummy variable *Enlaw* is formulated to represent the policy shock of the urban environmental legislation. Columns (1)-(3) of Table 5 present the estimation results excluding the aforementioned policy shocks. The findings indicate that all estimated coefficients are significantly negative, affirming that the results of this study remain robust even after adjusting for other pertinent policies concurrent in the analyzed period.

4.4.7. The inclusion of a benchmark variable mitigates the effects of selection

If the environmental targets are influenced by variables such as the city's economic development level, historical missions, and geographical location, the temporal evolution of these factors might differentially impact the *PCRE*. To mitigate the impact of non-random selection in targeting, we introduce an interaction term between the city's baseline characteristics and a linear time trend into Equation (1). This modification allows us to capture and adjust for the influence of underlying, time-varying differences among cities that might affect the treatment effect estimation. The revised model is formulated as follows:

$$PCRE_{it} = \alpha + \beta EG_{it} + \gamma X_{it} + \sigma Q_c Trend_t + \delta_i + \varphi_t + \varepsilon_{it} \quad (6)$$

Where Q represents a set of dummy variables for city benchmark factors, including attributes such as whether the city is within the 'two control zones', whether it is a provincial capital, and whether it is a special economic zone, among others. *Trend* denotes a linear time trend. After incorporating the interaction between the urban benchmark variables and the linear time trend, the coefficient estimates of *Target* remain statistically significant, passing the significance test at the 1 % level. Columns (1)-(4) of Table 6, robustness check confirms the efficacy of the Target in improving environmental outcomes, while also highlighting the importance of controlling for non-random

selection effects in the analysis.

4.4.8. Further verification based on PSM-DID method

The risk of endogeneity bias stemming from reverse causation is substantially reduced by the nature of the PCRE as an explained variable, which is unlikely to influence the core explanatory variable, environmental targets. The robustness through PSM-DID of our findings is underscored by the statistical significance of the coefficient estimates of *Target*, which remain significant at the 1% level across various matching methods employed—namely, the nearest neighbor matching, kernel matching, and radius matching methods (columns (1) to (3) of table 7). These results corroborate the effectiveness of environmental targets in reducing pollution and carbon emissions, further affirming that the observed effects are not artifacts of model specification but reflect genuine causal relationships.

4.4.9. Endogenous treatment: IV approach

To address potential endogeneity, this study employs an instrumental variable (IV) approach, using a city's natural river density derived from geographic information. We acknowledge the reviewer's insightful point regarding historical industrial development along rivers. However, we posit that in the context of contemporary China's environmental regulation and urban development, the direct relevance of natural river density to current economic activities at the prefecture level is limited. Our justification for its exogeneity is threefold:

First, regarding relevance. River density is positively associated with the urban watershed area and the number of state-controlled environmental monitoring sites, which increases public and regulatory oversight on environmental performance, thereby satisfying the relevance condition.

Second, regarding exogeneity. The core of our identification strategy rests on the geographic and pre-determined nature of river density. This natural endowment is historically formed and independent of contemporary prefecture-level economic decisions or shocks. While rivers did historically facilitate industry, modern industrial layout in Chinese cities is predominantly shaped by policy planning and infrastructure rather than natural waterways alone. To further alleviate concerns that river density might capture residual effects of historical development, we have controlled for a set of historical covariates (e.g. historical industrial base from the earliest available data) in our robustness checks. The exclusion restriction relies on the argument that, conditional on these controls and our baseline controls, river density affects contemporary PCRE primarily through the channel of enhanced monitoring and public pressure, rather than through unobserved economic confounders.

Third, regarding empirical evidence. The results are reported in Columns (4)-(5) of Table 7. The results of the first stage of the 2SLS analysis reveals that the coefficient estimate for the IV on the potentially endogenous variable is 0.0668. This estimate is statistically significant at the 1% level, affirming a strong correlation between the IV and the suspected endogenous variable, with the correlation direction aligning with the theoretical expectations. Additionally, the robustness of the instrumental variable is further supported by the Cragg-Donald Wald F-statistic, which stands at 64.89. This value comfortably exceeds the commonly accepted thresholds used to rule out the presence of weak instruments, thereby rejecting the hypothesis that the instruments are weak and might not provide valid identification.

In the second stage of the analysis, the core parameters are found to be statistically significant at the 1% level and retain the same sign as observed in the benchmark regression. This consistency underscores that even after accounting for potential endogeneity through the instrumental variable

approach, the conclusions remain consistent with those of the benchmark model. Thus, the analysis provides robust evidence supporting the initial findings, reinforcing the credibility of the study's conclusions regarding the impact of environmental governance targets on pollution and carbon reduction.

4.5. Heterogeneity analysis

4.5.1. Heterogeneity of urban resource endowments

According to the "Notice of National Sustainable Development Plan for Resource Cities (2013-2020)," cities are categorized into resource cities (116 in total) and non-resource cities. The findings presented in columns (1) and (2) of Table 8 examines the differential effects of environmental targets based on these categories. The results indicate that environmental targets significantly reduce emissions in non-resource cities but have a negligible impact on resource cities. The lesser effect observed in resource cities can likely be attributed to their heavier reliance on local resource endowments, which leads to a lock-in effect. This specialization discourages the growth and diversification into other industrial sectors, which hinders the progression toward greener development practices. On the other hand, non-resource cities, which are more economically diversified and market-oriented, show a greater inclination toward environmental quality. This inclination is further supported by the public's higher motivation to engage in environmental monitoring under environmental targets, pushing for an industrial upgrade and the adoption of green technologies, thus facilitating more effective emission reductions.

4.5.2. Heterogeneity of city size

In this research, cities are categorized into two groups—large cities and small to medium-sized cities—based on the criteria set by the "Notice on Adjusting the Standard for the Division of City Size" issued by China in 2014. The regression analyses are displayed in columns (3) and (4) of Table 8. The objectives exert a more pronounced impact on fostering the emission reduction effect in small and medium-sized cities than in large cities. This variation can be attributed to the already well-established and mature innovation capacities of large cities, where the marginal effects of environmental targets initiatives are diminishing, thus contributing less to their advancement. Conversely, small and medium-sized cities exhibit a greater responsiveness to emission reduction initiatives due to their still-untapped potential for emission decreases.

4.5.3. Heterogeneity in degree of marketisation

This paper explores the heterogeneous effects of environmental targets on emission reductions across regions with varying degrees of marketization. To measure the degree of regional market integration, this study utilizes the marketization index from the "China Sub-Provincial Marketization Index Report," using 2010 as the baseline year. Regions with marketization indices above the median are categorized as having high market integration, while those below the median are considered to have low market integration.

The findings presented in columns (1) and (2) of Table 9 indicate that environmental targets markedly enhance emission reductions in regions characterized by a high degree of marketization. In contrast, these targets have a negligible effect on emission reductions in regions with minimal marketization. This disparity can be ascribed to the enhanced competitive and operational efficiency prevalent in highly marketized environments. The regions with low levels of marketization often lack the economic vitality and necessary infrastructure to effectively enact and derive benefits from environmental directives, resulting in a minimal impact on emission reductions.

4.5.4. Heterogeneity of low carbon policies

This paper analyses the heterogeneity of the sample cities into those that have implemented low-carbon policies and those that have not, based on whether the city has implemented low-carbon city pilot policies or carbon emissions trading mechanisms. The results are shown in columns (3) and (4) of Table 9. It is found that the emission reduction effect of environmental objectives is more significant in cities that have not implemented low-carbon policies than in cities that have implemented low-carbon policies.

The observed variation in the effectiveness of environmental objectives across cities can be attributed to several interconnected factors. Firstly, cities without specific low-carbon policies often begin from a higher emission, thereby providing a broader scope for significant reductions under general environmental objectives. In contrast, cities that have already implemented such policies typically start with lower emission levels, which narrows the potential for drastic further decreases. Secondly, in cities with advanced low-carbon initiatives, such as carbon trading systems or pilot low-carbon city projects, the incremental benefits of additional environmental objectives tend to diminish. This occurs because these cities are likely already near the optimum level of their emissions strategies, leaving little room for further significant improvements from new policies. This issue can significantly affect the overall impact of new environmental objectives, as continuous enforcement struggles to adapt to an evolving regulatory landscape.

4.5.5. Heterogeneity of the Hu Line

This study focuses on evaluating the influence of environmental goals on pollution control and carbon emission reduction in cities situated along both sides of the Hu Line. Columns (1) and (2) of Table 10 present the estimated impacts of environmental goals on cities situated on the eastern and western sides of the Hu Line, respectively. The findings indicate that environmental objectives significantly influence emission reductions in cities east of the Hu Line. In contrast, these objectives appear less effective in reducing carbon emissions in the western cities. This disparity may be attributed to the higher levels of urbanization in the eastern cities, which facilitate enhanced utilization of digital information technology. Consequently, these advancements improve emission efficiency and contribute to overall emission reductions.

4.5.6. Heterogeneity of local officials

In examining the role of environmental objectives in the context of official promotions, this paper uses the tenure of prefecture-level city officials in 2010 as a benchmark. Cities with tenures longer than the median are classified as having high promotion pressure, while those with shorter tenures are considered to have low promotion pressure. The findings, presented in columns (3) and (4) of Table 10, reveal that environmental targets significantly reduce emissions in cities facing high promotion pressure but do not have a notable impact on those with low promotion pressure. Officials with longer tenures, who face high promotion pressure, typically prioritize 'significant indicators' like economic performance, which are more sustainable in terms of development. This focus leads them to adopt a 'moderately proactive' stance towards environmental policies.

Moreover, the environmental protection assessment and accountability systems, including the 'one-vote veto' mechanism, lack sufficient deterrent power to enforce stringent environmental governance. This situation is exacerbated by the 'government game,' where short-term officials prioritize GDP targets over environmental goals. Consequently, this leads to a decline in the effectiveness of environmental governance and contributes to regulatory challenges, including the manipulation of local statistics to meet targets a phenomenon described as 'numbers out of officials' and 'officials out of numbers,' highlighting the disconnect between official reports and actual

environmental outcomes.

5. Extensibility Analysis

5.1 Mechanisms analysis

To elucidate the mechanisms underlying the observed variations in pollution and carbon reduction attributable to disparate environmental objectives, we propose the following econometric model:

$$M_{it} = \alpha + \beta EG_{it} + \gamma X_{it} + \delta_i + \varphi_t + \varepsilon_{it} \quad (12)$$

Where M refers to the mechanism variable, which encompasses the variables through which environmental objectives exert influence on the outcomes related to pollution mitigation and carbon reduction efforts. In the selection of mechanism variables, this study identifies four distinct types based on the theoretical mechanisms discussed in the preceding section.

Firstly, Porter's competition effect catalyzes more vigorous innovation behaviors, which in turn facilitates the advancement of emission reduction technologies. The natural logarithm of the number of invention patents filed in each prefecture-level city within a given year, denoted as *Patent*, serves as a proxy for the degree of innovation activity. The estimation results are detailed in column (1) of Table 11. These results indicate that the estimated coefficients are statistically significant at the 1% level, confirming the hypothesized relationship.

Second, to examine whether the environmental objective will lead to higher green development through industrial greening and factor endowment structure. Both industrial greening and factor endowment structures will reduce pollution and carbon emissions. The estimation results are presented in column (2) of Table 11, where the core estimates demonstrate a significant positive effect at the 1% significance level, suggesting that environmental objectives positively influence credit activities. The restructuring of factor endowments is quantified primarily through the ratio of capital stock to labor force, expressed on a logarithmic scale. The core findings are documented in column (3) of Table 11, showing that these estimates are also significantly positive at the 1% level of significance, indicating a positive relationship between environmental objectives and the structure of factor endowments.

Finally, the investigation assesses whether environmental objectives contribute to emission reductions within the region through scale effects. Under the constraints imposed by these objectives, local governments, producers, and the public are compelled to decrease energy consumption through a variety of methods. The regression findings are detailed in column (4) of Table 11. It is observed that the impact of environmental objectives on per capita electricity consumption is negative and achieves statistical significance at the 5% level. Overall, the mechanistic analyses result above verify the Hypothesis 2.

5.2 Spatial spillover effects

Environmental targeting strategies employed by local governments should be spatially relevant, influencing emission reduction efforts in adjacent regions. When local governments prioritize short-term economic growth through tactical and adaptive strategies, competitive pressures may prompt neighboring governments to emulate these actions, potentially leading to increased emissions in those regions.

Considering the negative externality of regional emissions and the strategic interactive behaviour of local government target management, then there may be spatial correlation between environmental emission reduction among cities, and target management behaviour among local governments. Therefore, we firstly adopt Moran index to carry out spatial autocorrelation test to

verify whether there is spatial correlation. Figure 4, reports the Moran test using the spatial neighbourhood matrix. It is found that Moran's index (Moran's I) is greater than 0, and the p-values are all less than 0.01, indicating that emission reduction has strong spatial correlation.

Table 12 presents the estimation outcomes from the Spatial Durbin Model (SDM). The findings indicate that the spatial autoregressive coefficient (ρ) is significantly positive, signifying a notable positive spatial spillover in emission reductions among cities. This pattern implies that when emissions in neighboring cities increase, they also rise in the focal city. LeSage and Pace (2009) noted a certain bias in spatial regression models when using point estimation methods to ascertain the presence of spatial spillovers. Therefore, we adopt the methodology proposed by Elhorst (2014) to decompose the impact of each factor on emission reduction into direct and indirect effects. The estimation results, as displayed in columns (4)-(6) of Table 12, reveal that the estimated coefficients for the direct, indirect, and total effects are significantly negative. This indicates that while environmental target management effectively reduces emissions within the city, it also produces positive externalities for neighboring cities, thereby reducing emissions in those areas as well, which bears out the Hypothesis 3.

6. Conclusions and policy implications

The environmental targets can restrain the government's actions, so it is of great significance to evaluate the effect of environmental targets. This paper aims to explore the impact of government environmental targets on regional pollution reduction and carbon reduction effects, along with its underlying mechanisms. The main conclusions of this paper are as follows: (1) The implementation of environmental targets by local governments significantly contributes to pollution reduction and carbon reduction. These conclusions remain robust even after constructing instrumental variables to control endogeneity and conducting various robustness tests. (2) Heterogeneity analyses show that the pollution and carbon reduction effects of environmental targets are more significant in cities east of the Hu line, smaller-sized cities, non-resource cities, cities with long tenure of officials, cities with high degree of marketisation, and cities that have not implemented low-carbon policies. (3) Further extended analyses show that environmental objectives can enhance the reduction effect through four channels: technological innovation, industrial greening, green credit, and energy consumption. Moreover, the spatial Durbin model analysis indicates a positive correlation between the reduction effect of environmental targets, suggesting significant positive spatial spillovers in emission reduction among cities.

Based on these findings, the paper proposes the following policy implications: First, local governments should continue to set and strengthen binding quantitative environmental targets, as our baseline results and event-study evidence show that such targets generate statistically significant and economically meaningful synergistic reductions in both pollution and carbon emissions. To maximize long-term effectiveness, these targets must be incorporated into the formal cadre performance evaluation system with sufficient weight and a "one-vote veto" mechanism, rather than remaining declarative goals.

Second, the central government should implement strongly differentiated guidance and support policies. Our heterogeneity analysis reveals that environmental targets are markedly less effective in resource-dependent cities, primarily due to fiscal constraints and locked-in industrial structures. Therefore, for these regions, the central government should provide special transfer payments, green transformation funds, and technical assistance to support industrial diversification and prevent

excessive economic slowdown while still achieving environmental goals.

Third, policy design must prioritize true synergy between pollution and carbon reduction rather than treating them as separate tasks. Our mechanism tests confirm that technological innovation, industrial structure greening, and energy efficiency improvement are the dominant channels. Accordingly, future policy packages should move beyond end-of-pipe treatment and instead bundle hard environmental targets with green credit expansion, R&D subsidies for clean technology, and accelerated phase-out of backward production capacity, this integrated approach will reinforce the three channels simultaneously and avoid the "pollution reduction without carbon reduction" trap observed in some cities.

Fourth, regional coordination mechanisms must be established to internalize positive spatial spillovers and prevent strategic pollution transfer. Our spatial Durbin model results and decomposition of direct/indirect effects provide robust evidence of significant positive spillovers to neighboring cities after 2013, reflecting the shift from "race to the bottom" to centrally driven "race to the top". To further amplify these benefits, the central government should institutionalize joint prevention and control mechanisms across provincial and municipal boundaries, establish shared monitoring platforms, and include cross-regional environmental performance in the evaluation of provincial leaders.

In the course of empirical analysis, several shortcomings have been identified in this paper: Firstly, the research interval is relatively short due to data limitations, which may restrict the generalizability of the findings. Future research should aim to validate and complement these findings over a broader and more recent research period. Secondly, the paper lacks further distinction between micro firms, particularly in terms of how local government environmental objectives impact the emission effects of industrial firms. Future research could investigate into this aspect to provide a more nuanced understanding of the relationship between environmental objectives and firm-level emissions. Lastly, while the paper focuses on examining whether environmental objectives lead to regional pollution and carbon reduction effects and their mechanisms, it falls short in providing a detailed delineation of the intensity and mode of environmental objectives.

Ethics Declarations;

Competing Interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Ethics Approval and Consent to Participate

This study did not involve human participants, animal subjects, or any other activities requiring formal ethical approval.

Consent for Publication

All participants provided informed consent for publication of anonymized data.

Credit Author Statement;

Shubo Yang: Methodology and Analysis & Revision

Chao Li: Project Administration

Ting Xu: Supervision Graphics & Designs and Data Collection

Muhammad Adnan Bashir: Write Original Draft

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Availability of Data and Materials

Data are available from the corresponding author upon reasonable request.

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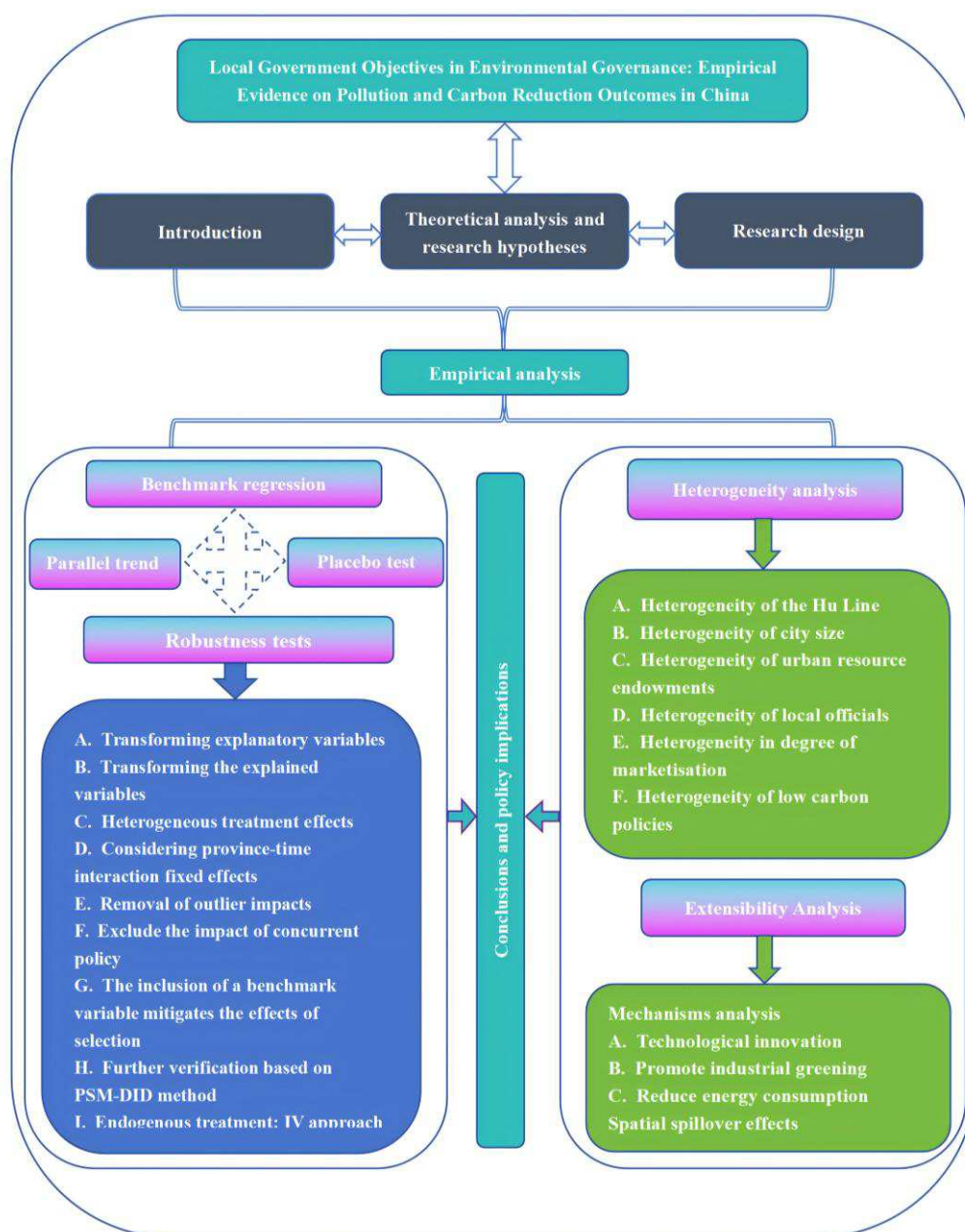


Figure 1. Framework structure of the paper

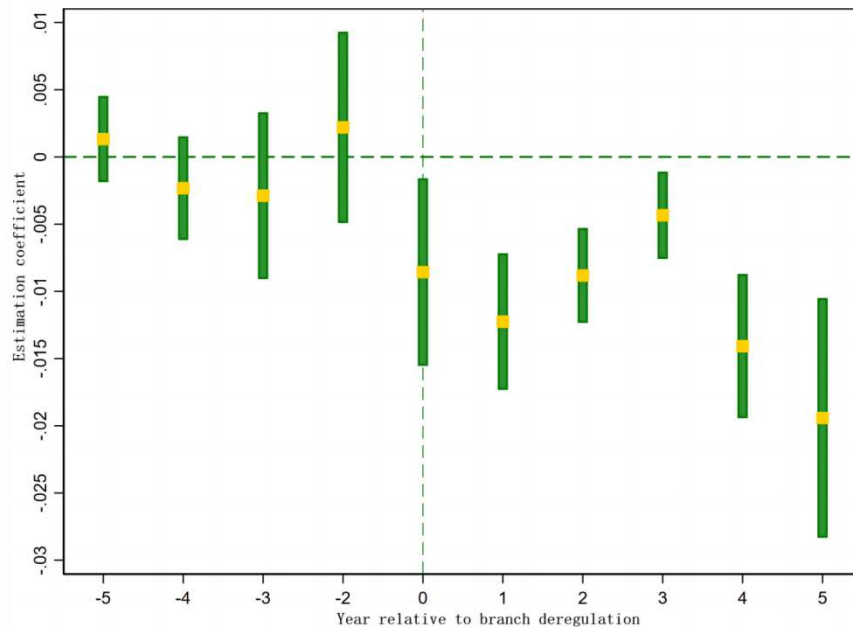


Figure 2. Coefficient diagram of the parallel trend test

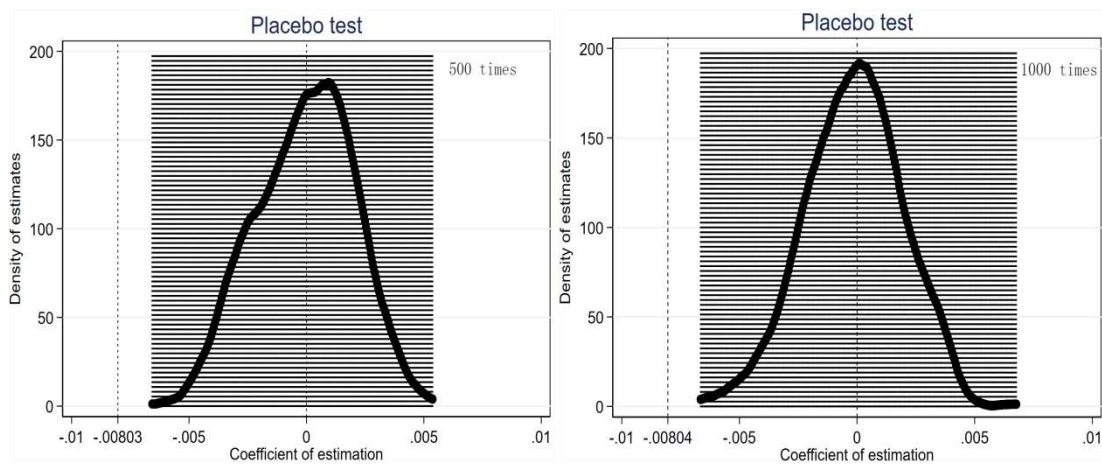


Figure 3. Distribution of estimated coefficients for randomly selected experimental groups

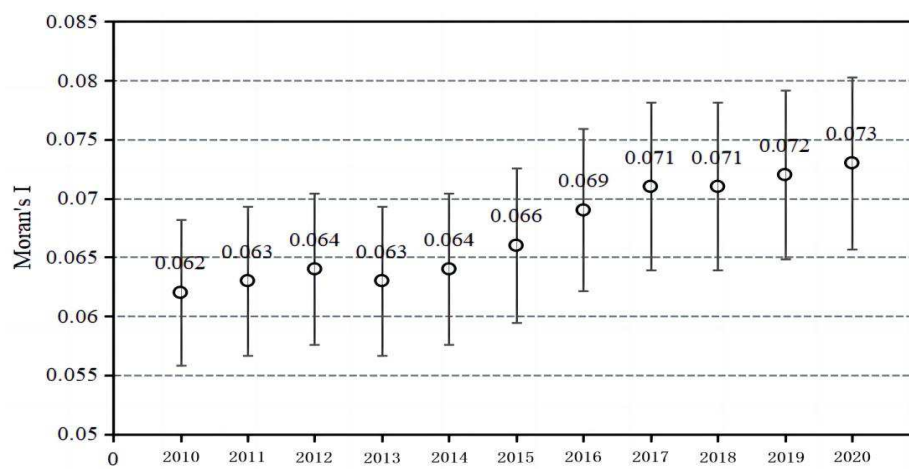


Figure 4. Results for Moran's I

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Table 1 Descriptive statistics

Variable	Obs	Mean	Std.Dev	Min	Max
PCRE	2343	0.079	0.078	0.000	0.954
Target	2343	0.204	0.403	0	1
IS	2343	0.466	0.121	0.095	0.898
ED	2343	10.657	0.593	8.576	12.579
PD	2343	0.043	0.037	0.000	0.779
LO	2343	0.028	0.027	0.000	0.299
FD	2343	0.143	0.073	0.037	2.010
TI	2343	0.027	0.027	0.001	0.631
CB	2343	15.50	1.10	5.48	18.89

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Table 2 Basic regression results

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Target	-0.00526*	-0.00498*	-0.00348*	-0.00417*	-	-	-	-
					0.00832*	0.00886*	0.00869*	0.00871*
					**	**	**	**
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
IS		0.0193**	0.0119**	0.0100**	0.00690*	0.00669*	0.00670*	0.00669*
		*	*	*	**	**	**	**
		(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
ED			0.0596**	0.0611**	0.0442**	0.0389**	0.0395**	0.0391**
			*	*	*	*	*	*
			(0.005)	(0.005)	(0.004)	(0.005)	(0.005)	(0.005)
PD				0.005	0.007	0.004	0.005	0.005
				(0.044)	(0.033)	(0.033)	(0.033)	(0.033)
LO					0.052	0.048	0.051	0.050
					(0.034)	(0.034)	(0.034)	(0.034)
FD						-0.0755**	-0.0746**	-0.0732**
						(0.034)	(0.034)	(0.034)
TI							-0.0374	-0.0372
							(0.027)	(0.027)
CB								0.002
								(0.002)
Constant	-	-0.171***	-0.769***	-0.775***	-0.576***	-0.508***	-0.513***	-0.542***
	0.0784**							
	*							
	(0.001)	(0.007)	(0.053)	(0.052)	(0.041)	(0.051)	(0.051)	(0.057)
City-FE	Y	Y	Y	Y	Y	Y	Y	Y
Year-FE	Y	Y	Y	Y	Y	Y	Y	Y
N	2343	2343	2343	2343	2343	2343	2343	2343
R2	0.853	0.864	0.872	0.878	0.906	0.906	0.906	0.907

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Note:(1) The values enclosed in parentheses represent robust standard errors; (2) The significance levels are denoted by asterisks: *** indicates a significance level of 1%, ** a significance level of 5%, and * a significance level of

10%; (3) N is the sample size, and R2 is the goodness of fit. The same as below.

Table 3 Results of Robustness Tests I

Variables	(1)PCRE	(2)SO2	(3)wastewater
Target		-0.0118*	-0.185***
		(0.007)	(0.033)
Target pressure	-0.0255***		
	(0.006)		
IS	0.002	-0.00893**	-0.0677***
	(0.002)	(0.004)	(0.021)
ED	0.0436***	-0.0115	0.0912
	(0.010)	(0.017)	(0.081)
PD	-0.279	-0.109	0.227
	(0.287)	(0.122)	(0.563)
LO	0.015	0.196	1.741***
	(0.050)	(0.121)	(0.581)
FD	-0.0582	-0.368***	2.354***
	(0.056)	(0.120)	(0.579)
TI	-0.0455	-0.0149	0.356
	(0.028)	(0.099)	(0.470)
CB	-0.00208	0.0123*	0.0154
	(0.002)	(0.007)	(0.035)
Constant	-0.264*	-2.244***	-6.057***
	-0.00208	(0.317)	(1.583)
City-FE	Y	Y	Y
Year-FE	Y	Y	Y
N	2343	2343	2343
R2	0.936	0.883	0.895

Table 4 Results of Robustness Test II

Variables	(1)	(2)	(3)
Target	-0.00810***	-0.0103***	-0.00775***
	(0.002)	(0.002)	(0.002)
IS	0.00602***	0.00856***	0.00968***
	(0.001)	(0.001)	(0.001)
ED	0.0650***	0.0293***	0.0354***
	(0.003)	(0.005)	(0.005)
PD	-0.0893***	-0.0111	0.00804
	(0.028)	(0.034)	(0.032)
LO	-0.00476	0.0166	0.0309
	(0.033)	(0.037)	(0.034)
FD	0.0306	-0.0890**	-0.0872**
	(0.020)	(0.038)	(0.037)
TI	-0.114***	-0.0296	-0.0112

	(0.035)	(0.027)	(0.028)
CB	0.0103***	0.000541	0.000964
	(0.002)	(0.002)	(0.002)
Constant	-1.220***	-0.298***	-0.414***
	(0.021)	(0.099)	(0.096)
City-FE	Y	Y	Y
Year-FE	Y	Y	Y
N	2343	2343	2127
R2	0.656	0.919	0.918

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878 **Table 5 Results of Robustness Test III**

Variables	(1)	(2)	(3)
Target	-0.00851***	-0.00679***	-0.00279***
	(0.002)	(0.002)	(0.002)
IS	0.00657***	0.00753***	0.00726***
	(0.001)	(0.001)	(0.001)
ED	0.0394***	0.0364***	0.0375***
	(0.005)	(0.005)	(0.005)
PD	0.005	0.017	0.007
	(0.033)	(0.032)	(0.032)
LO	0.0458	0.0158	-0.012
	(0.034)	(0.034)	(0.034)
FD	-0.0725**	-0.107***	-0.126***
	(0.034)	(0.034)	(0.033)
TI	-0.0365	-0.0104	-0.00323
	(0.027)	(0.027)	(0.027)
CB	0.00207	0.00129	0.000837
	(0.002)	(0.002)	(0.002)
<i>Fiscal</i>	0.003		
	(0.003)		
<i>Pollutant</i>		-0.00409***	
		(0.005)	
<i>Enlaw</i>			-0.00349***
			(0.005)
Constant	-0.544***	0.798***	0.275
	(0.058)	(0.162)	(0.173)
City-FE	Y	Y	Y
Year-FE	Y	Y	Y
N	2343	2343	2343
R2	0.907	0.91	0.907

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880 **Table 6 Results of Robustness Test IV**

Variables	(1)	(2)	(3)	(4)
Target	-0.00621***	-0.00629***	-0.00829***	-0.00513***

	(0.002)	(0.002)	(0.002)	(0.002)
IS	0.00715***	0.00767***	0.00727***	0.00734***
	(0.001)	(0.001)	(0.001)	(0.001)
ED	0.0390***	0.0390***	0.0390***	0.0389***
	(0.005)	(0.005)	(0.005)	(0.005)
PD	0.009	0.015	0.007	0.008
	(0.032)	(0.032)	(0.033)	(0.032)
LO	0.011	0.025	0.038	0.013
	(0.034)	(0.034)	(0.034)	(0.034)
FD	-0.103***	-0.0997***	-0.0905***	-0.108***
	(0.034)	(0.034)	(0.034)	(0.034)
TI	-0.0198	-0.0232	-0.0323	-0.02
	(0.027)	(0.027)	(0.027)	(0.027)
CB	0.002	0.002	0.002	0.002
	(0.002)	(0.002)	(0.002)	(0.002)
<i>Two control zones</i>	-0.00225***			-0.00204***
	(0.003)			(0.003)
<i>Provincial capitals</i>		-0.00305***		-0.00262***
<i>or not</i>		(0.001)		(0.001)
<i>Special economic</i>			0.00215*	0.00214*
<i>zone or not</i>			(0.001)	(0.001)
Constant	2.174***	0.133	-0.464***	2.310***
	(0.404)	(0.136)	(0.101)	(0.408)
City-FE	Y	Y	Y	Y
Year-FE	Y	Y	Y	Y
N	2343	2343	2343	2343
R2	0.91	0.909	0.908	0.911

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Table 7 Results of Robustness Test V

Variables	(1)l:n	(2)kernel	(3)radius	(4)Phase I	(5)Phase II
Target	-0.00804***	-0.00793***	-0.00699***		-0.0431***
	(0.002)	(0.002)	(0.002)		(0.016)
IV				0.0668***	
				(0.008)	
IS	0.00736***	0.00729***	0.00761***	-0.0302***	0.00401***
	(0.001)	(0.001)	(0.001)	(0.007)	(0.001)
ED	0.0391***	0.0395***	0.0423***	0.106***	0.0711***
	(0.005)	(0.005)	(0.005)	(0.025)	(0.004)
PD	0.012	0.013	0.016	-0.589**	-0.0903***
	(0.033)	(0.033)	(0.031)	(0.244)	(0.030)
LO	0.032	0.031	0.023	-0.841***	-0.0678*
	(0.034)	(0.034)	(0.033)	(0.272)	(0.039)
FD	-0.0910***	-0.0918***	-0.0334	-0.096	0.023
	(0.034)	(0.035)	(0.035)	(0.162)	(0.021)

TI	-0.0284 (0.027)	-0.0292 (0.027)	-0.0265 (0.026)	0.911*** (0.287)	-0.0883** (0.042)
CB	0.002 (0.002)	0.002 (0.002)	0.004 (0.003)	0.067*** (0.019)	0.0143*** (0.003)
Constant	-0.391*** (0.092)	-0.394*** (0.092)	-0.538*** (0.096)	-1.826*** (0.182)	-1.320*** (0.042)
City-FE	Y	Y	Y	Y	Y
Year-FE	Y	Y	Y	Y	Y
N	2220	2209	2052	2221	2221
R2	0.908	0.906	0.909	0.408	0.606
CD-Wald F				64.89	64.89

Table 8 Heterogeneity of urban resource endowments and city size

Variables	(1)	(2)	(3)	(4)
Target	-0.00589 (0.004)	-0.00892*** (0.002)	-0.00358** (0.002)	-0.00707** (0.003)
IS	0.00855*** (0.002)	0.00565*** (0.001)	0.00274** -0.0012	0.00916*** -0.00165
ED	0.0563*** (0.010)	0.0249*** (0.005)	0.0367*** (0.005)	0.0489*** (0.007)
PD	-1.812*** (0.654)	0.00984 (0.028)	0.0231 (0.017)	-0.644*** (0.235)
LO	-0.143 (0.089)	0.0813** (0.033)	0.0485** -0.0247	0.055 -0.0568
FD	-0.352*** (0.086)	0.0145 (0.033)	0.108*** (0.036)	-0.0777* (0.046)
TI	-0.0192 (0.038)	-0.0446 (0.043)	0.011 (0.041)	-0.0163 (0.034)
CB	-0.00172 (0.003)	0.00791** (0.004)	0.000375 -0.00115	0.0103** -0.00511
Constant	-0.593*** (0.113)	-0.481*** (0.074)	-0.467*** (0.054)	-0.780*** (0.095)
City-FE	Y	Y	Y	Y
Year-FE	Y	Y	Y	Y
N	852	1491	832	1511
R2	0.914	0.901	0.893	0.905
Difference in coefficient P-value				0.039*

Note: The p-value for the test of coefficient group differences for heterogeneity analysis was calculated using the Fisher's combined test (1000 samples). The results of the test based on the seemingly uncorrelated model are also similar to those of the Chou test.

Table 9 Heterogeneity of marketisation and low carbon policies

Variables	(1)	(2)	(3)	(4)
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Target	-0.00747*** (0.002)	-0.00405 (0.004)	0.00633 (0.004)	-0.00872*** (0.002)
IS	0.00679*** (0.001)	0.00654*** (0.002)	(0.002) (0.003)	0.00679*** (0.001)
ED	0.0287*** (0.005)	0.0563*** (0.010)	0.011 (0.007)	0.0437*** (0.005)
PD	0.0105 (0.025)	-1.216** (0.547)	-0.306 (0.207)	-0.0015 (0.038)
LO	0.150*** (0.035)	-0.145* (0.075)	-0.0126 (0.079)	0.0392 (0.037)
FD	0.0474 (0.034)	-0.310*** (0.081)	0.00999 (0.069)	-0.0845** (0.038)
TI	-0.0219 (0.032)	-0.042 (0.046)	0.0177 (0.031)	-0.0734** (0.034)
CB	0.00696* (0.004)	-0.0000792 (0.003)	0.00327 (0.004)	0.00218 (0.002)
Constant	-0.522*** (0.070)	-0.619*** (0.115)	-0.190* (0.099)	-0.591*** (0.065)
City-FE	Y	Y	Y	Y
Year-FE	Y	Y	Y	Y
N	1278	1065	202	2017
R2	0.9	0.911	0.925	0.909

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891 **Table 10 Heterogeneity of the Hu Line and local officials**

Variables	(1)	(2)	(3)	(4)
Target	-0.0104*** (0.002)	0.012 (0.009)	-0.00920*** (0.002)	-0.00763 (0.005)
IS	0.00780*** (0.001)	-0.0199*** (0.006)	0.00712*** (0.001)	0.00772** (0.003)
ED	0.0408*** (0.005)	0.010 (0.023)	0.0390*** (0.005)	0.0419*** (0.014)
PD	0.0053 (0.032)	0.137 (2.650)	0.0137 (0.032)	0.366 (0.548)
LO	0.0432 (0.034)	0.195 (0.264)	0.0341 (0.040)	0.0847 (0.094)
FD	-0.0676** (0.034)	-0.176 (0.194)	-0.045 (0.039)	-0.0913 (0.093)
TI	-0.0546 (0.035)	-0.00231 (0.049)	-0.0533 (0.038)	-0.0543 (0.051)
CB	0.00217 (0.002)	0.0116 (0.013)	0.00232 (0.002)	0.0326** (0.016)
Constant	-0.566*** (0.059)	-0.255 (0.289)	-0.549*** (0.064)	-1.068*** (0.253)
City-FE	Y	Y	Y	Y

Year-FE	Y	Y	Y	Y
N	2086	257	1587	756
R2	0.908	0.924	0.912	0.92

Table 11 Regression results of mechanistic analyses

Variables	(1)Patent	(2)industrial greening	(3)factor endowment	(4)energy consumption
Target	0.307*** (0.065)	0.00595*** (0.002)	0.252*** (0.024)	-0.0411** (0.016)
IS	0.0692* (0.041)	-0.00706*** (0.001)	-0.00286 (0.015)	0.0508*** (0.010)
ED	0.674*** (0.158)	0.0577*** (0.003)	-0.330*** (0.060)	-0.334*** (0.039)
PD	1.074 (1.156)	0.468*** (0.136)	-0.223 (0.430)	-0.373 (0.284)
LO	-2.893** (1.143)	-0.0948*** (0.034)	-1.132*** (0.427)	-0.418 (0.286)
FD	-5.776*** (1.131)	0.357*** (0.026)	-6.333*** (0.423)	-0.682** (0.283)
TI	6.563*** (0.929)	0.0224 (0.027)	1.599*** (0.348)	0.108 (0.229)
CB	-0.0971 (0.070)	0.0106*** (0.002)	0.00807 (0.026)	-0.0456*** (0.018)
Constant	-3.603* (1.928)	-0.496*** (0.027)	5.713*** (0.726)	-4.445*** (0.479)
City-FE	Y	Y	Y	Y
Year-FE	Y	Y	Y	Y
N	2343	2343	2343	2343
R2	0.958	0.951	0.94	0.844

Table 12 Spatial Durbin model regression results

Variables	(1)Main	(2)Wx	(3)Spatial	(4)LR_Direct	(5)LR_Indirect	(6)LR_Total
Target	-0.0153** (0.017)	-0.4475*** (0.171)		-0.0276* (0.018)	-0.2158* (1.140)	-0.2185* (1.144)
IS	0.0086*** (0.003)	-0.1271*** (0.049)		0.0064* (0.004)	-0.5473 (0.373)	-0.5409 (0.375)
ED	-0.1062*** (0.021)	-1.3030*** (0.191)		-0.1284*** (0.022)	-6.3466** (3.045)	-6.4750** (3.055)
PD	-0.0141*** (0.004)	-0.0877** (0.038)		-0.0158*** (0.004)	-0.4583 (0.288)	-0.4741* (0.288)
LO	0.0079 (0.005)	-0.2930*** (0.056)		0.0028 (0.005)	-1.3075** (0.569)	-1.3047** (0.571)
FD	0.4280*** (0.044)	1.6836*** (0.426)		0.4655*** (0.046)	9.2222** (4.344)	9.6877** (4.359)

TI	-0.2270*** (0.025)	-0.5268*** (0.203)		-0.2204*** (0.026)	1.6826 (1.160)	1.4622 (1.161)
CB	0.7492*** (0.101)	-0.0653 (0.421)		0.7816*** (0.223)	8.5565 (56.532)	9.338 (56.730)
ρ			0.7669*** (0.060)			
City-FE	Y	Y	Y	Y	Y	Y
Year-FE	Y	Y	Y	Y	Y	Y
N	2343	2343	2343	2343	2343	2343
R2	0.279	0.279	0.279	0.279	0.279	0.279

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