

Article

Can Urban Regeneration Initiatives Enhance the Synergistic Effect of Pollution and Carbon Reduction? Evidence from China

Haiyan Ye, Tao Lyu *, Kaixin Zheng and Chongling Chen

China-ASEAN School of Economics & School of Economics & China-ASEAN Institute of Financial Cooperation, Guangxi University, Nanning 530004, China; 2023100414@st.gxu.edu.cn (H.Y.); 2330301069@st.gxu.edu.cn (K.Z.); 2023100303@st.gxu.edu.cn (C.C.)

* Correspondence: taolv@gxu.edu.cn

Abstract

During the accelerated transition toward greener and more decarbonized development, urban regeneration initiatives have emerged as an important policy instrument for enhancing the synergistic effect of pollution and carbon reduction (SEPCR). Using panel data for 282 prefecture-level-and-above cities from 2006 to 2022, this study exploits the Ecological Restoration and Urban Repair (ERUR) pilot as an exogenous policy shock and applies a multi-period DID framework to identify its impact on SEPCR. The results show that the ERUR policy significantly enhances SEPCR by approximately 1.9%, and the findings remain robust across multiple robustness checks, including parallel trend tests, stacked DID, and double machine learning. Heterogeneity analyses reveal that policy effects differ across cities with varying geographical locations, resource endowments, industrial characteristics, and spatial forms. Mechanism analyses suggest that the improvement in SEPCR is primarily driven by economies of scale, industrial structure upgrading, and energy intensity improvement. This study extends the quantitative assessment framework of SEPCR and provides robust empirical evidence on how urban regeneration initiatives can be systematically harnessed to enhance urban SEPCR performance, offering important academic insights and policy-relevant implications for promoting green transformation, urban sustainable development, and ecological civilization construction.

Keywords: urban regeneration; ecological restoration and urban repair; synergistic effect; pollution reduction; carbon emission reduction

Academic Editor: Xing Wu

Received: 18 December 2025

Revised: 3 February 2026

Accepted: 4 February 2026

Published: 9 February 2026

Copyright: © 2026 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

Currently, environmental deterioration and climate change pose simultaneous and increasingly severe challenges worldwide. Rising concentrations of greenhouse gases have accelerated global temperature increases and intensified extreme climatic events, while persistent regional and compound air pollution continues to undermine human health and ecological resilience. These challenges are closely interconnected, since human activities like fossil fuel combustion and industrial production are major sources of greenhouse gases such as carbon dioxide (CO₂), as well as pollutants including sulfur dioxide (SO₂), nitrogen oxides (NO_x), and particulate matter (PM) [1]. This overlap in sources and emission processes implies that traditional policy frameworks characterized by

fragmented governance and single-objective regulation may entail high implementation costs, efficiency losses, and even offsetting policy effects [2]. Consequently, a transition toward a more systemic, integrated, and coordinated governance approach has become an inevitable policy choice. Against this backdrop, the concept of SEPCR has emerged and has gradually gained broad recognition in environmental governance [3]. SEPCR is theoretically rooted in the notion of “co-benefits” introduced by Ayres and Walter in 1991, which emphasizes that climate mitigation policies can simultaneously reduce emissions of traditional air pollutants [4]. The IPCC incorporated the idea of co-benefits in its Third Assessment Report and further emphasized the multi-objective synergies of policy interventions in its Fifth Assessment Report, thereby providing theoretical grounding for coordinated pollution–carbon governance. In recent years, empirical studies have examined SEPCR across a range of environmental regulatory instruments, offering accumulating evidence on the practical feasibility of such coordinated governance [5].

The process of urbanization and the accompanying urban regeneration initiatives constitute a critical context through which the effectiveness of SEPCR is shaped. Cities, as centers of population, economic activity, and social interaction, account for approximately 70% of global energy-related carbon emissions [6]. Urban spatial form, functional structure, infrastructure efficiency, and development patterns fundamentally determine the ultimate effectiveness of SEPCR [7]. As the global urbanization rate has exceeded 50%, the world has entered a new phase of urbanization focused on enhancing the quality and efficiency of existing urban spaces. Urban regeneration has become one of the core means to drive the green and sustainable urban transformation. In addition, the scope of urban regeneration has evolved from a narrow focus on reconstruction and redevelopment toward a more comprehensive approach emphasizing ecological restoration, inclusiveness, resilience, and sustainability [8]. China, as a key emerging economy and one of the world’s major sources of carbon emissions, has experienced rapid industrialization and urbanization while facing mounting environmental pressures and the need to transform its development model. China’s urbanization rate surpassed 50% in 2011 and exceeded 67% by 2024. The previous growth model driven by extensive spatial expansion has generated a range of urban challenges, including resource constraints, environmental pollution, and increasingly frequent extreme heat events. These challenges have made urban regeneration an essential pathway for achieving greener and more sustainable urban development.

To address these challenges, China has formally articulated the “30·60” dual-carbon goals at the national strategic level. It has also identified coordinated progress in carbon reduction, pollution control, ecological improvement, and economic development as a key pathway toward ecological civilization and high-quality growth. Moreover, an integrated urban regeneration approach, known as ERUR, was introduced in 2015. The ERUR policy emphasizes incremental and systematic spatial interventions aimed at restoring degraded natural ecosystems and repairing missing or inefficient urban functions. In doing so, it seeks to alleviate human–land relationship tensions arising from rapid urbanization, including spatial shortages, ecological degradation, loss of urban character, and land-use imbalances, thereby improving environmental quality and enhancing urban functionality [9]. Beginning with the designation of Sanya as the first national pilot city in 2015, the ERUR policy has been progressively implemented nationwide, providing a valuable quasi-natural experimental setting for examining whether and how urban regeneration initiatives can enhance SEPCR.

Early studies on pollutant emissions and carbon emissions largely followed separate research paths. Pollution-related studies initially focused on single indicators such as SO₂ and PM_{2.5}, and later shifted toward composite pollution indices, with increasing attention to multi-pollutant coordinated control and related health effects [10]. In contrast, carbon emissions research expanded from aggregate emission control to efficiency assessment,

analysis of driving factors, and the examination of spatial interaction effects [11]. Although the research focuses differ, both strands share similar theoretical foundations and analytical frameworks, particularly in their discussion of key drivers such as economic agglomeration, thereby providing an important basis for research on SEPCR. Recent studies suggest that policies such as low-carbon city pilots, carbon emissions trading, and pollution permit trading can enhance SEPCR through industrial and energy structure transformation [12]. However, most existing studies focus on sector-specific or single-objective pilot and market-based policies, while other studies examine intervention targets such as infrastructure development or urban agglomeration in isolation [13]. By contrast, the ERUR program represents a comprehensive urban regeneration initiative. It improves urban quality through spatial restructuring, functional reconfiguration, infrastructure upgrading, and the reshaping of social networks. Its effects on SEPCR and the underlying mechanisms remain insufficiently explored. Urban regeneration is essentially a profound process of spatial reorganization. Its impacts may differ from those of conventional environmental or economic regulatory policies, as it can more directly affect the built environment, residents' lifestyles, and the spatial configuration of economic activities. Accordingly, a key research gap arises. Can comprehensive urban regeneration initiatives, as exemplified by the ERUR policy, significantly enhance SEPCR? If so, through what mechanisms, and with what heterogeneous effects? Addressing these questions is crucial for improving urban regeneration policy design and maximizing its environmental benefits.

Therefore, this study employs panel data from China's 282 prefecture-level-and-above cities over the period 2006–2022 to examine the effects of the ERUR policy on SEPCR. The potential marginal contributions of this study can be summarized as follows. First, the study advances measurement strategies by constructing an integrated framework that captures both pollution and carbon reduction. By combining the Super-SBM model with the coupling coordination degree model, the study provides a systematic measure of SEPCR and its dynamic evolution over time. Second, the ERUR policy is embedded within the analytical framework of urban regeneration initiatives. Using a multi-period DID model, the study provides causal evidence of the synergistic environmental effects of urban regeneration policies. Third, through heterogeneity and mechanism analyses, the study highlights the context-dependent nature of policy impacts, considering geographical location, resource endowments, industrial characteristics, and urban spatial form. It identifies three key channels—economies of scale, industrial structure upgrading, and energy intensity improvement. Overall, this study enriches the literature on spatial policy instruments by clarifying how urban regeneration initiatives contribute to SEPCR. The findings provide empirically grounded insights that can inform coordinated pollution-carbon governance and improve environmental governance systems in China and beyond.

This paper is organized as follows. Section 2 reviews the related literature. Section 3 presents the theoretical analysis and develops the research hypotheses. Section 4 describes the methods and data sources. Section 5 reports the empirical results. Section 6 provides further analysis, including heterogeneity analysis and mechanism testing. Finally, Section 7 presents the conclusions. The research framework is illustrated in Figure 1.

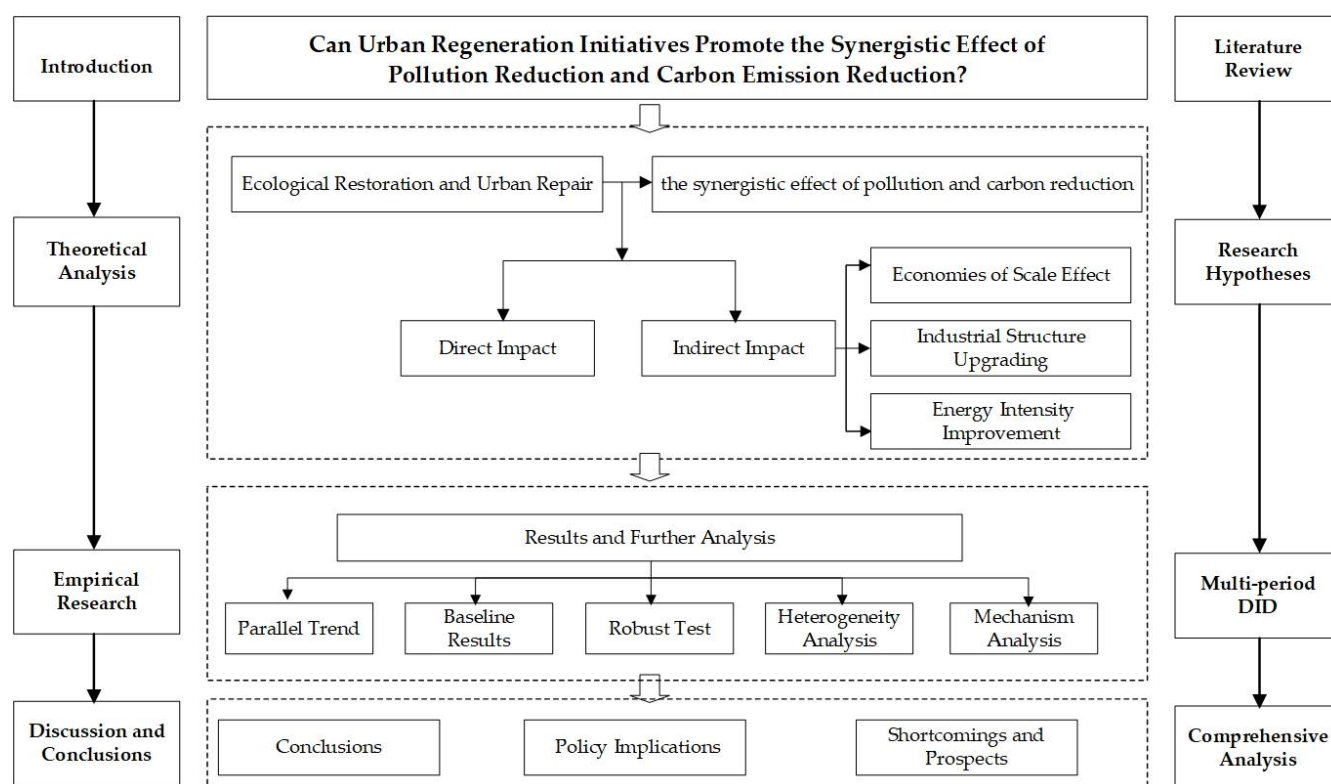


Figure 1. Research Framework.

2. Literature Review

Reviewing the existing literature, studies directly relevant to this research can be classified into three categories: independent studies on pollution reduction systems or carbon reduction systems, studies on synergistic pollution and carbon reduction governance, and studies on urban regeneration initiatives.

The first category of the literature focuses on pollution abatement and carbon mitigation as independent research domains, typically treating them as two separate systems and analyzing them in isolation. Regarding pollution reduction, existing studies mainly examine the control of atmospheric pollutants such as SO_2 , $\text{PM}_{2.5}$, and NO_x . Indicators including pollutant emissions and concentration levels are commonly used to assess environmental quality [14,15]. In terms of carbon emission reduction, the literature primarily relies on indicators such as total CO_2 emissions, per capita carbon emissions, and carbon emission intensity. These measures are widely applied to evaluate carbon emission efficiency and have been extended to related areas such as green innovation [16–18]. In addition, many studies have incorporated pollution reduction systems [19] or carbon mitigation systems [20] into the Environmental Kuznets Curve (EKC) framework to explore the relationships between economic growth and environmental outcomes from these two perspectives.

The second category of the literature mainly investigates the feasibility, evaluation methods, and driving factors of SEPCR. First, existing research has provided evidence for the presence of synergistic effects across multiple dimensions, including emission sources, spatial distribution, and governance effectiveness. For example, Liu et al. (2020) found that CO_2 and various air pollutants share 22 common pathways among the top 100 major emission routes [21]. Wang et al. (2021) showed that a reduction of 1000 tons of industrial carbon emissions can lead to a simultaneous decrease of 1 ton of composite air pollutant emissions [22]. Zheng et al. (2018) further verified that air pollution control policies promote carbon emission reduction [23]. Second, a wide range of methods has been employed to measure SEPCR. These include correlation coefficient evaluation approaches [24],

entropy-based methods and index construction [25], nonlinear programming models [26], super-efficiency SBM models combined with inverse DEA methods [27], as well as coupling coordination degree models integrated with spatial analysis [28]. Third, with regard to influencing factors, energy regulation and innovation [29], digital economy growth [30], and the development of green digital financial systems [31] have been shown to exert positive effects on SEPCR. Building on the premise that coordinated governance enables environmental policies to address multiple objectives simultaneously, an expanding literature has further explored the synergy-enhancing effects of policy implementation. Empirical evidence suggests that a variety of environmental policy instruments—including low-carbon city pilots [32], carbon trading policies [33], pollution discharge fee policies [34], renewable energy policies [35], and “zero-waste” city initiatives [36]—can effectively promote SEPCR. Finally, existing studies generally find that the synergistic effects generated by such policies are not limited to administrative boundaries but instead diffuse spatially across regions. Positive spillovers are mainly realized through technological spillovers, knowledge diffusion, industrial linkages, and demonstration and competition effects associated with regional collaborative governance [37]. In contrast, negative spillovers primarily stem from regional disparities in environmental regulation. These disparities may induce a “pollution haven” effect, whereby polluting or carbon-intensive industries relocate from regions with stricter regulatory regimes to those with comparatively lenient regulations [38]. Notably, the ERUR policy differs fundamentally from conventional policies that focus on industrial adjustment, energy transition, or market-based regulation, while also complementing them. ERUR takes urban space as its primary carrier and emphasizes systematic restoration [39]. By improving both natural and built environmental quality, it enhances SEPCR from the perspectives of adaptation and optimization of existing urban stocks. Unlike policies such as low-carbon city pilots or renewable energy demonstrations, which mainly target source-based emission reduction, ERUR places greater emphasis on integrated end-of-pipe capacity enhancement and process optimization. As a result, its spatial spillover mechanisms extend beyond traditional technological or industrial diffusion. They also encompass ecological connectivity, landscape demonstration effects, and the joint construction of regional ecological security patterns, thereby offering a novel pathway for enhancing SEPCR.

The third category of the literature explores urban regeneration and its related studies. As a core strategy for sustainable urban transformation, urban regeneration facilitates efficient resource allocation, mitigates urban decline, and upgrades urban spatial structures [40]. It functions as a lever for urban spatial governance while delivering environmental benefits through targeted interventions within the urban fabric. With the acceleration of urbanization and rising public expectations for higher-quality living conditions, the objectives of urban regeneration have moved beyond the traditional model of large-scale slum clearance. Instead, urban regeneration has evolved toward an integrated framework that combines old district revitalization, ecological greening, and functional enhancement [41,42]. Related research has expanded to a variety of specific contexts, including territorial spatial governance [43], urban road planning [44], micro-renewal of urban villages [45], soil erosion control and conservation [46], and the transformation of ecological resources into economic value [47]. From a global perspective, urban regeneration practices differ markedly across stages of development. In Europe and North America, regeneration efforts have primarily concentrated on revitalizing deteriorating urban areas and modernizing infrastructure. By contrast, most cities in developing countries, including China, remain in a phase of development-oriented transformation. Rapid urbanization has generated a set of common challenges, including ecological degradation, infrastructure shortages, deterioration of the built environment, and rising pollution emissions [48]. Against this backdrop, China’s ERUR practice adopts systematic ecological

interventions and spatial optimization to achieve multiple objectives simultaneously. These objectives encompass improvements in environmental quality, enhanced SEPCR performance, and stronger urban competitiveness. By integrating environmental restoration with urban development, ERUR directly addresses the core concern of developing countries to balance economic growth with ecological protection, highlighting its distinctive value in advancing urban green transformation. However, the environmental effects of urban regeneration have not yet reached a clear consensus in the literature. Previous studies have reported potential positive [49], negative [50], nonlinear [51], and even insignificant relationships [52] between urbanization and carbon emissions. Notably, research that treats the ERUR policy as a policy shock within the context of urban regeneration remains relatively limited. According to Zhao et al. (2024), the ERUR policy yields a significant improvement in land-use carbon efficiency, although the effect becomes evident only after two years [9].

In summary, prior studies provide valuable theoretical insights for this research, while leaving several issues unresolved. Most prior research examines carbon emissions or air pollutants separately, with limited attention to multi-pollutant synergies and integrated environmental outcomes. Similarly, studies on urban regeneration initiatives largely rely on qualitative analysis, and relatively few quantitatively assess SEPCR. Addressing unresolved issues in the existing literature, this study conducts a comprehensive empirical investigation into how urban regeneration initiatives influence SEPCR.

3. Theoretical Analysis

3.1. Spatiotemporal Patterns of Pollution and Carbon Emissions in China

The ERUR policy was officially launched in 2015. To identify the stylized facts of pollution and carbon emissions before and after its implementation, data on industrial SO₂ and CO₂ emissions from the year preceding the policy launch (2014) to the end of the sample period (2022) are examined. Spatial maps are generated using ArcGIS 10.8.1, where the natural breaks classification method is applied to visualize and compare the spatiotemporal changes in the two types of emissions, as depicted in Figure 2. The spatial pattern of SO₂ emissions reveals that, over time, the emission range in 2022 was substantially narrower than that in 2014, and both the total emission level and the high-emission threshold declined significantly, indicating a strong constraining effect of pollution-control efforts. Spatially, high SO₂-emission zones remained concentrated in the industrialized regions of East China and North China. However, the pollution intensity within these hotspots was markedly reduced. While spatial clustering persisted, the overall scale of pollution substantially contracted. In contrast, the spatiotemporal dynamics of CO₂ emissions exhibit different characteristics. Temporally, the overall emission range expanded between 2014 and 2022. While total emissions increased, the rise in the high-emission threshold was relatively moderate, implying that carbon reduction constraints may have slowed, but not reversed, emission growth. Spatially, the distribution of CO₂ emissions remained relatively stable. North and East China consistently exhibited high-emission levels, whereas western regions maintained comparatively low emissions. This spatial path dependence reflects persistent interregional differences in economic performance, sectoral composition, and patterns of energy use. In high-emission regions, carbon reduction efforts were closely linked to industrial restructuring and energy efficiency improvements. Nevertheless, the upward shift in the emission range suggests that ongoing structural transformation has yet to fully offset emission growth. In contrast, western regions with lower emission baselines appear more capable of advancing carbon reduction in conjunction with ecological conservation.

Taken together, the differentiated spatiotemporal patterns of SO₂ and CO₂ emissions reveal two key features of SEPCR. First, pollution reduction has generally progressed

more rapidly than carbon reduction. SO₂ emissions have been effectively curtailed through end-of-pipe control technologies, which are relatively easy to implement and yield immediate results. Carbon reduction, by contrast, depends on deep transformations of industrial structures and energy systems, making progress more gradual. Second, pollution and carbon emissions exhibit substantial spatial overlap, as high-emission regions are often also pollution hotspots. Consequently, regulatory actions targeting energy-intensive industries are likely to generate simultaneous reductions in pollution and carbon emissions, highlighting the inherent spatial synergy underlying SEPCR.

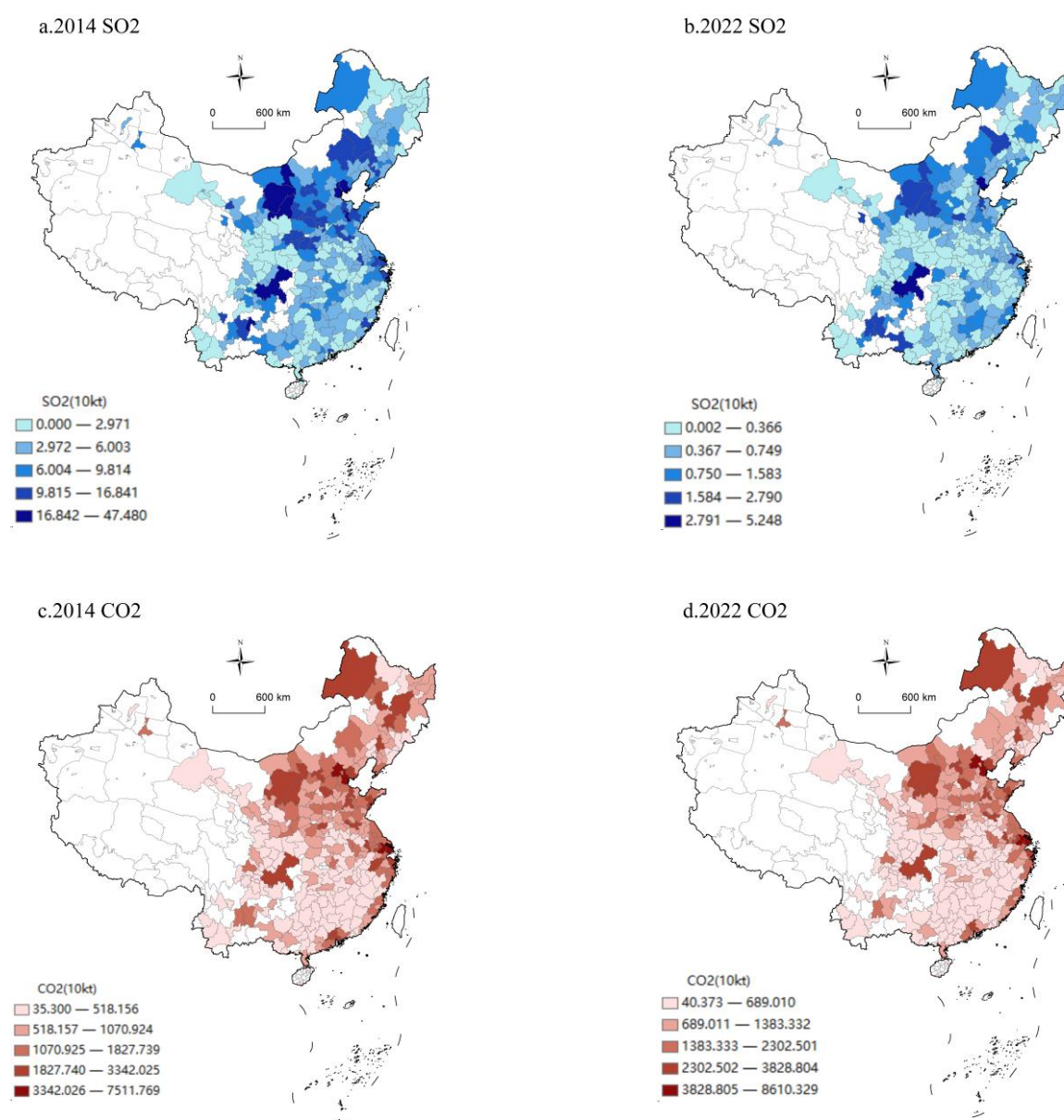


Figure 2. Spatiotemporal Patterns of SO₂ and CO₂ in China. Note: The map is based on the standard map of the National Administration of Surveying, Mapping and Geoinformation (Approval No. GS(2024)0650), the base map was not modified, the same applies below.

3.2. *The Direct Impact of ERUR on SEPCR*

As an important policy instrument for advancing urban sustainability, the ERUR initiative influences SEPCR primarily by integrating ecological restoration with comprehensive urban repair actions. Ecological restoration focuses on the systematic rehabilitation of degraded ecosystems, with particular attention to water bodies, green spaces, and mountainous areas. By optimizing ecological spatial structures and improving connectivity within ecological networks, this approach increases the carbon sequestration potential of forests, wetlands, and soil systems. At the same time, natural processes such as vegetation photosynthesis and microbial degradation enable the simultaneous promotion of carbon sequestration and pollutant removal [43]. Urban repair, by contrast, targets structural deficiencies in the built environment, including spatial disorder and outdated infrastructure. By shifting away from energy-intensive urban expansion, enhancing human-managed carbon sinks, and improving energy structures, urban repair facilitates the optimization of existing urban space and the development of green infrastructure. These measures improve resource utilization efficiency and public service provision while reducing carbon emissions and pollutant generation at the source [40]. In summary, the ERUR policy establishes an ecological foundation through ecological restoration and provides contextual support through urban repair. Together, these two pathways form an integrated support system linking natural and built environments. By strengthening carbon sequestration capacity and curbing emissions at their origin, the policy guides urban development toward a cleaner, low-carbon, and higher-quality pathway, thereby providing institutional and practical support for the realization of SEPCR objectives. Accordingly, Hypothesis 1 is proposed:

H1. *The ERUR policy can enhance SEPCR in cities.*

3.3. *Mechanism Analysis of ERUR on SEPCR*

3.3.1. Economies of Scale Effect

According to the EKC, in the early stages of economic development, economic growth is accompanied by rising resource consumption and pollutant emissions, leading to environmental degradation. After income surpasses a certain turning point, environmental quality gradually improves due to technological progress, industrial upgrading, and increased environmental awareness, forming an inverted U-shaped relationship. Some studies further propose an N-shaped EKC, emphasizing that environmental pressure may rise again in the absence of sustained policy intervention. This highlights the critical role of structural policies in achieving long-term environmental improvement [53].

As a comprehensive spatial governance initiative aimed at promoting high-quality urban development, the ERUR policy facilitates SEPCR through two interrelated stages: advancing the EKC turning point and consolidating the post-turning-point trajectory. In both stages, the economic scale effect serves as a key transmission mechanism. Before the EKC turning point, ERUR strengthens the urban development foundation through the coordinated implementation of ecological restoration and urban repair. Ecological restoration rehabilitates degraded ecosystems and enhances the carbon sequestration and pollution reduction capacities of natural sinks such as forests and wetlands, thereby directly reducing pollutant and greenhouse gas emissions. At the same time, urban repair improves the built environment by promoting green infrastructure and upgrading existing urban space. This process replaces energy-intensive and highly polluting facilities and curbs incremental emissions from urban operations. Together, these interventions enhance environmental carrying capacity and spatial quality, attract high-end factors such as capital, technology, and talent, and generate a virtuous cycle of factor attraction, aggregation, and diffusion [45], thereby creating favorable conditions for economic expansion.

After the EKC turning point, the economic scale effect further releases SEPCR benefits through multiple channels. First, at the technological level, economic agglomeration fosters dense innovation networks and market demand, encouraging firms to upgrade green processes and products and accelerating the diffusion and application of green technologies [17]. Second, at the institutional level, economic development promotes the integration of environmental objectives into local governance and official evaluation systems. This strengthens environmental regulation, raises entry barriers, and forces the transformation of highly polluting and carbon-intensive firms [54]. Third, at the resource allocation level, factor agglomeration improves allocation efficiency and resource utilization. Meanwhile, infrastructure sharing and centralized governance under economies of scale reduce the marginal costs of pollution control, enabling coordinated source-based reductions in pollutants and greenhouse gas emissions [6]. In summary, by following the evolutionary logic of the EKC, the ERUR policy provides a systematic theoretical foundation and practical pathway for achieving SEPCR during the process of urban economic growth. Based on this, Hypothesis 2 is proposed:

H2. *The ERUR policy enhances SEPCR in cities through the economies of scale effect.*

3.3.2. Industrial Structure Upgrading

With ecological restoration and urban repair as its dual core, the ERUR policy systematically drives the transformation of urban development patterns from extensive expansion to qualitative enhancement. It establishes a solid spatial and ecological foundation for industrial structure adjustment and green upgrading. On the supply side, the ERUR policy generates implicit environmental regulation by enhancing ecological carrying capacity and restructuring urban spatial functions. Ecological restoration improves ecosystem stability and self-purification capacity, while urban repair optimizes the built environment and land use efficiency. Together, these measures increase compliance costs and operational pressures on high-pollution and high-energy-consumption industries [55]. As their development models conflict with the policy's green orientation, traditional high-emission and overcapacity industries face shrinking profit margins and tighter resource constraints, leading some enterprises to relocate, transform, or exit the market [56]. This process releases key production factors, including land and capital, which can be reallocated toward low-pollution, high value-added green industries, thereby facilitating industrial agglomeration, technological diffusion, and industrial structure upgrading from the upstream of production. On the demand side, the ERUR policy significantly enhances urban ecological livability and residents' quality of life. Ecological restoration improves the accessibility and ecosystem service functions of green spaces and water bodies, while urban repair upgrades public service facilities and the overall living environment. These improvements increase residents' willingness to pay for high-quality ecological environments and strengthen preferences for green consumption, stimulating demand for green goods and services [57]. In response to these demand-side signals, firms are incentivized to incorporate environmental considerations into strategic decision-making and adjust production processes to enhance green competitiveness, thereby promoting industrial upgrading through demand-pull mechanisms [58]. In summary, by integrating supply-side structural reforms with demand-side guidance, the ERUR policy advances green industrial transformation and contributes to the realization of SEPCR. Drawing on the above theoretical discussion, Hypothesis 3 is proposed:

H3. *The ERUR policy enhances SEPCR in cities by facilitating industrial structure upgrading.*

3.3.3. Energy Intensity Improvement

Lower energy intensity is essential for advancing SEPCR in cities. Prior studies indicate that a 1% increase in energy intensity is associated with an approximately 0.27% rise in carbon emissions, underscoring the fundamental role of energy efficiency improvement in enhancing environmental performance [59]. Under the ERUR policy framework, the coordinated implementation of ecological restoration and urban repair provides multiple pathways for reducing energy intensity. Ecological restoration creates spatial platforms for renewable energy deployment, such as distributed photovoltaic and biomass systems. At the same time, urban repair enhances the capacity to absorb and integrate clean energy by upgrading infrastructure and advancing smart grid development. This integration lowers dependence on high-carbon energy sources, increases the penetration of clean energy in urban systems, and promotes the restructuring or phase-out of energy-intensive sectors [33]. In addition, the ERUR policy promotes cleaner energy consumption by fostering green industrial clusters. Such industries generally exhibit lower energy intensity while generating relatively high value added. Their agglomeration directly reduces regional energy intensity and indirectly improves energy efficiency in traditional industries through technology spillovers and economies of scale, jointly reducing air pollutants and CO₂ emissions [35]. Moreover, the integration of green technologies with existing energy systems enhances energy allocation and utilization efficiency through dynamic monitoring and optimized scheduling, further reducing energy input per unit of economic output and strengthening synergistic pollution and carbon reduction effects [29]. In summary, by reshaping urban energy structures and improving energy efficiency, the ERUR policy contributes to lower energy intensity and provides systematic support for achieving SEPCR and advancing urban green and low-carbon transformation. Thus, Hypothesis 4 is proposed:

H4. *The ERUR policy enhances SEPCR through improvements in energy intensity.*

4. Research Design

4.1. Model Setting

To evaluate the impact of urban regeneration initiatives on SEPCR, this study treats the ERUR policy as a quasi-natural experiment and employs a multi-period DID for causal identification. The estimations are performed using Stata 18.0. The baseline model is specified as follows:

$$SEPCR_{it} = \alpha_1 + \beta_1 ERUR_{it} + \theta_1 X_{it} + \mu_i + \delta_t + \varepsilon_{it} \quad (1)$$

In Equation (1), $SEPCR_{it}$ represents the level of SEPCR for city i in year t . $ERUR_{it}$ indicates whether the ERUR policy was implemented in city i in year t . X_{it} represents a series of control variables that may affect SEPCR, including the economic development level ($\ln pgdp$), population density (pop), financial development (fin), government intervention (gov), and communication scale (CS). μ_i and δ_t denote city fixed effects and year fixed effects, respectively, and ε_{it} is the random disturbance term.

4.2. Variable Selection

4.2.1. Explained Variable

The measurement of SEPCR follows a two-step empirical framework. First, indicators are selected from an input–output perspective to construct an evaluation system (Table 1). The Super-SBM model with undesirable outputs is subsequently applied to measure pollution reduction efficiency (PRE) and carbon reduction efficiency (CRE) at the city level using DEArun software, as specified in the following equation [27].

$$\min \rho = \frac{\frac{1}{m} \sum_{i=1}^m (\bar{x}/x_{ik})}{\frac{1}{r_1 + r_2} (\sum_{s=1}^{r_1} \bar{y}^d/y_{sk}^d + \sum_{q=1}^{r_2} \bar{y}^u/y_{qk}^u)}$$

$$\left\{ \begin{array}{l} \bar{x} \geq \sum_{j=1, \neq k}^n x_{ij} \lambda_j; \bar{y}^d \leq \sum_{j=1, \neq k}^n y_{sj}^d \lambda_j; \bar{y}^u \geq \sum_{j=1, \neq k}^n y_{qj}^u \lambda_j; \\ \bar{x} \geq x_k; \bar{y}^d \leq y_k^d; \bar{y}^u \geq y_k^u; \lambda_j \geq 0; \\ i = 1, 2, \dots, m; j = 1, 2, \dots, n; \\ s = 1, 2, \dots, r_1; q = 1, 2, \dots, r_2; \end{array} \right. \quad (2)$$

Here, ρ represents either PRE or CRE. m , r_1 , and r_2 represent the numbers of input indicators, desirable output indicators, and undesirable output indicators, respectively. x , y^d , and y^u correspond to the elements in the input matrix, desirable output matrix, and undesirable output matrix, respectively. n denotes the sample size, which consists of 282 prefecture-level-and-above cities.

Table 1. Indicator Selection and Definitions of SEPCR.

Primary Indicator	Secondary Indicator	Description	
		PRE	CRE
Input	Fixed capital stock	Stock of urban fixed-asset investment at constant 2004 prices	
	Employment	Year-end number of employees in urban work units	
	Energy consumption	City-level energy consumption estimated by fitting the relationship between nighttime light intensity and provincial energy consumption [60,61]	
Desirable output	Built-up area	Built-up area of municipal districts	
	GDP	GDP at constant 2004 prices	
Undesirable output	Pollution Composite Index or CO ₂ Emissions	Pollution Composite Index, constructed using the entropy method based on indicators such as SO ₂ emissions, smoke and dust emissions, and PM _{2.5} concentration	CO ₂ Emissions from fossil fuel combustion, cement production, and natural gas combustion

In the second step, a coupling coordination degree model is adopted to construct a composite indicator of SEPCR. Traditional studies typically rely on pollutant and carbon emission indicators to capture changes in emission levels. Such approaches are unable to quantify the interaction between pollution reduction and carbon reduction, which may lead to a partial interpretation of policy effects. To address this limitation, the coupling coordination degree model treats PRE and CRE as two interrelated subsystems. The coupling degree (C) measures the strength of interaction between the subsystems, while the coordination degree (D) reflects the quality of their synergy. Combined with an index of comprehensive development, this framework provides an integrated characterization of system-level benefits, whereby the joint effect of coordinated governance exceeds the additive contributions of each subsystem. Following Liu et al. (2021) and Chen et al. (2023), the model is specified as follows [28,62]:

$$C = \frac{2\sqrt{PRE \times CRE}}{PRE + CRE} \quad (3)$$

$$T = a \times PRE + b \times CRE \quad (4)$$

$$SEPCR = \sqrt{C \times T} \quad (5)$$

Here, *PRE* and *CRE* represent the values of these indicators after range standardization. *C* denotes the coupling degree, and *T* is the composite coordination index. *a* and *b* are parameters whose values are undetermined (with $a = b = 0.5$, treating both systems as of equal importance). *SEPCR* represents the coordination degree. Considering that *SEPCR* reflects both the coupling relationship between *PRE* and *CRE*, as well as their development levels, it provides an integrated measure of *SEPCR*. Accordingly, the subsequent empirical analysis focuses on identifying the relationship between *ERUR* and *SEPCR*.

4.2.2. Explanatory Variable

In March 2015, China's Ministry of Housing and Urban–Rural Development officially launched the *ERUR* pilot program, designating Sanya as the first national pilot city. Following Sanya's notable implementation outcomes, the second and third batches of *ERUR* pilot cities were announced in March and July 2017, respectively, covering a total of 58 cities (Table 2). To mitigate confounding effects in the policy evaluation, this study excludes county-level cities, focusing exclusively on data from prefecture-level cities for the policy effect assessment, totaling 51 cities (as shown in Figure 3). The *ERUR* policy implementation year is treated as the baseline for the policy shock. The time dummy variable, *Post* = 1, marks the years post shock, while *Post* = 0 reflects the years prior to the shock. Additionally, the individual dummy variable *Treat* = 1 is defined for *ERUR* pilot cities, and *Treat* = 0 for non-pilot cities. It should be noted that, to account for potential implementation lags and reduce estimation bias, a mid-year cutoff rule is applied. Specifically, when the *ERUR* policy was implemented before June 30, it is regarded as taking effect in the same year; otherwise, it is regarded as taking effect in the following year [63]. Therefore, this study sets the pilot commencement year for the second batch of cities as 2017 and for the third batch as 2018.

Table 2. List of *ERUR* Pilot Cities.

Batch	Pilot Time	Cities
First Batch	March 2015	Sanya
Second Batch	March 2017	Fuzhou, Xiamen, Quanzhou, Zhangjiakou, Kaifeng, Luoyang, Xi'an, Yan'an, Nanjing, Ningbo, Harbin, Jingdezhen, Jingmen, Hulunbuir, Ulanhot, Guilin, Anshun, Xining, and Yinchuan
Third Batch	July 2017	Baoding, Qinhuangdao, Baotou, Arxan, Anshan, Fuyuan, Xuzhou, Suzhou, Nantong, Yangzhou, Zhenjiang, Huaibei, Huangshan, Sanming, Jinan, Zibo, Jining, Weihai, Zhengzhou, Jiaozuo, Luohe, Changyuan, Qianjiang, Changsha, Xiangtan, Changde, Huizhou, Liuzhou, Haikou, Zunyi, Kunming, Baoshan, Yuxi, Dali, Baoji, Golmud, Zhongwei, and Urumqi

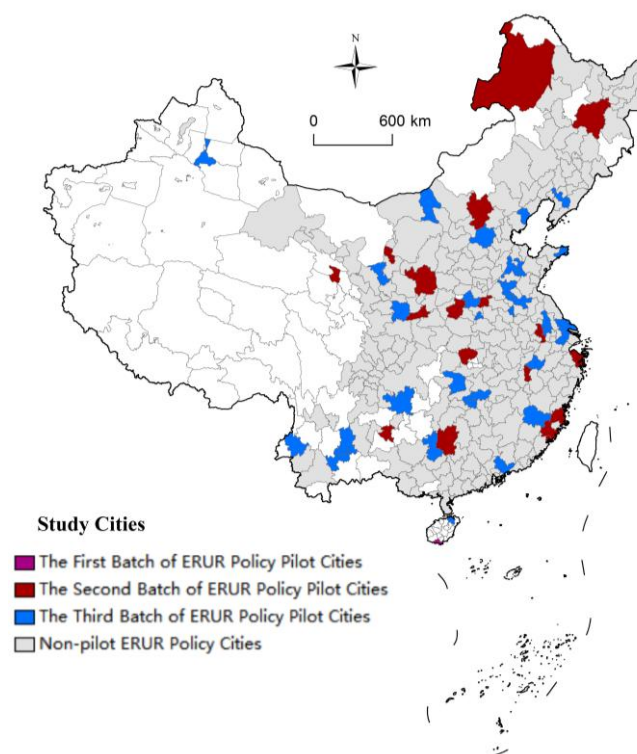


Figure 3. Study Cities.

4.2.3. Mechanism Variables

This study selects economic density, the industrial structure upgrading index, and energy intensity as core mechanism variables. The specific indicators are defined as follows. (a) Economic density (ED) is measured as the natural logarithm of GDP per unit of urban land area (10^4 CNY per square kilometer). (b) The industrial structure upgrading index (ind) is constructed based on the methodology proposed by Liu et al. (2024), by forming a vector based on the value-added shares of the primary, secondary, and tertiary sectors in GDP, and then computing the cosine similarity between this vector and a pre-defined benchmark vector [64]. (c) Energy intensity (energy) is defined as energy consumption per unit of GDP (tons of standard coal per 10^4 CNY).

4.2.4. Control Variables

The control variables are as follows: (a) Economic development level ($\ln pgdp$) is measured as the natural logarithm of real GDP per capita. Higher economic development generally implies stronger capital accumulation, technological capacity, and human resources, which may support SEPCR improvement. (b) Population density (pop) is measured by the number of permanent residents per square kilometer, capturing the degree of population concentration. Population agglomeration may affect resource utilization efficiency and the effectiveness of environmental governance. (c) Financial development (fin) is measured as the ratio of the year-end balance of deposits and loans of financial institutions to regional GDP. A more developed financial system can improve resource allocation efficiency and facilitate financing for pollution and carbon reduction projects. (d) Government intervention (gov) is proxied by the ratio of local general budgetary expenditures to general budgetary revenues. Fiscal intervention may strengthen policy implementation capacity through public spending and regulatory support. (e) Communication scale (CS) is measured by the number of mobile phone subscriptions at year-end (in units of 10,000). Well-developed communication infrastructure facilitates information diffusion,

cross-regional coordination, and regulatory efficiency, thereby potentially improving SEPCR outcomes.

4.3. Data Sources and Descriptive Statistics

Based on the principles of data availability and temporal continuity, prefecture-level cities with a high percentage of missing observations are excluded. The final sample consists of panel data for 282 prefecture-level-and-above cities over the period 2006–2022. The primary data sources include the EPS Global Statistical Data Platform, the China City Statistical Yearbook, and statistical yearbooks and annual economic and social development bulletins published by provincial and municipal governments. Nighttime light indicators are constructed by harmonizing DMSP-OLS and SNPP-VIIRS data, following the method proposed by Wu et al. (2021) [65]. PM_{2.5} concentration data are sourced from the China High-Resolution PM_{2.5} Dataset (2000–2023) provided by the National Tibetan Plateau Data Center, while CO₂ emissions data are obtained from the Center for Global Environmental Research (CGER). Missing observations are imputed using linear interpolation for a small subset of the data.

Before conducting the baseline regression, this study performs correlation analysis and VIF tests. The results indicate that VIF values for the primary variables are all well below 10, with a mean VIF of 2.18, also below 5, thereby mitigating the potential influence of multicollinearity. Table 3 summarizes the descriptive statistics for the main variables. Regarding the dependent variable, the maximum SEPCR value is 0.929, indicating that synergy between the PRE and CRE has not yet achieved full coordination. The minimum value is 0, suggesting that in some cities the two subsystems operate largely independently, with weak policy integration and an extreme imbalance between the subsystems. The mean SEPCR value is 0.498, with a standard deviation of 0.119, reflecting substantial heterogeneity in the effectiveness of coordinated pollution and carbon reduction governance across cities. With respect to the key explanatory variable, the mean value of ERUR is 0.058, implying that only a limited number of cities are covered by the ERUR policy, and the overall policy coverage remains relatively narrow. This highlights the need for a comprehensive empirical assessment of the impacts of such urban regeneration initiatives. Control variables exhibit considerable variation across cities, reflecting the reality of uneven regional development in China. The values of mechanism variables also exhibit significant differences, providing essential data support for subsequent examinations of the underlying transmission mechanisms of policy impacts.

Table 3. Descriptive Statistics.

Variables	Obs	Mean	SD	Min	Max
SEPCR	4794	0.498	0.119	0	0.929
PRE	4794	0.285	0.141	0	1
CRE	4794	0.242	0.112	0	1
ERUR	4794	0.058	0.233	0	1
lnpgdp	4794	10.537	0.711	7.921	12.456
pop	4794	476.966	603.842	5.166	8854.081
fin	4794	2.377	1.178	0.504	21.297
gov	4794	2.910	1.958	0.649	18.399
CS	4794	418.321	479.352	15	4433
ED	4794	7.045	1.346	2.190	11.996
ind	4794	5.514	0.204	4.867	6.260
energy	4794	2.693	1.559	0.237	21.200

4.4. Trend Analysis

Figure 4 depicts the progression of SEPCR differences across the treatment and control groups, as well as relative to the national average, before and after the policy was enacted. The results show that the gap between the treatment and control groups increases steadily over time, with a noticeable acceleration after the second round of large-scale urban pilot programs in 2017. The difference between the treatment group and the national average remains positive and shows a sustained upward trend, indicating that pilot cities consistently outperform the national SEPCR average. In contrast, the gap between the control group and the national average is negative and continues to widen, suggesting persistently lower SEPCR levels in non-pilot cities. Overall, these trends provide initial evidence that the ERUR policy may improve SEPCR, a proposition that is examined more rigorously in the subsequent analysis.

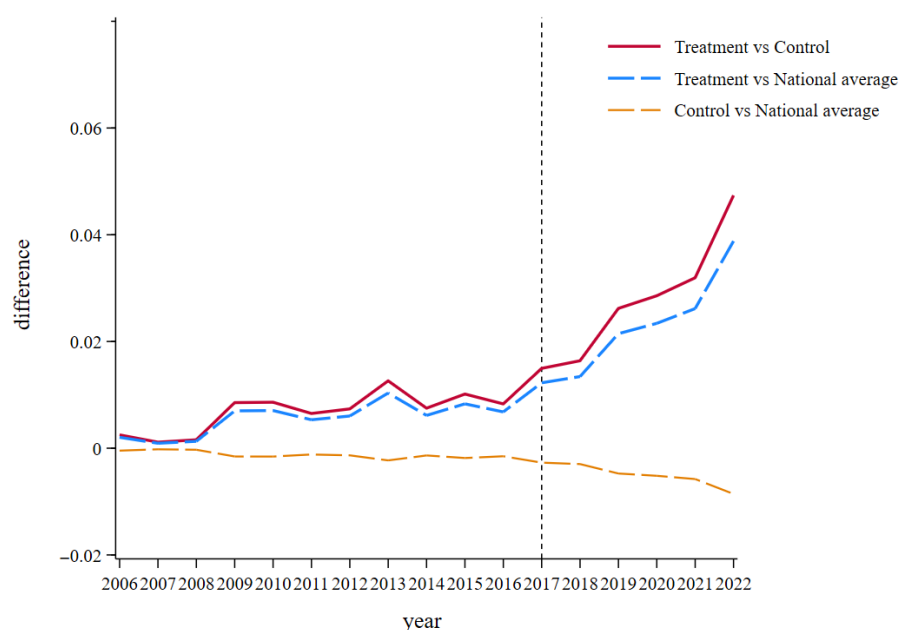


Figure 4. Trends Analysis Results.

5. Results

5.1. Parallel Trend

This study uses the year immediately before ERUR policy implementation as the baseline year and defines an event window of four years before and after the policy. Observations more than four years prior to implementation are grouped into period -4 , while those beyond four years after implementation are classified into period 4. Figure 5 illustrates the dynamic effects of the ERUR policy on SEPCR. The results indicate that, before policy implementation, the estimated coefficients are statistically insignificant and mostly hover around zero, suggesting that the treatment and control groups follow parallel trends in SEPCR. After implementation, the coefficients rise steadily over time, implying that the ERUR policy is associated with a sustained enhancement in SEPCR.

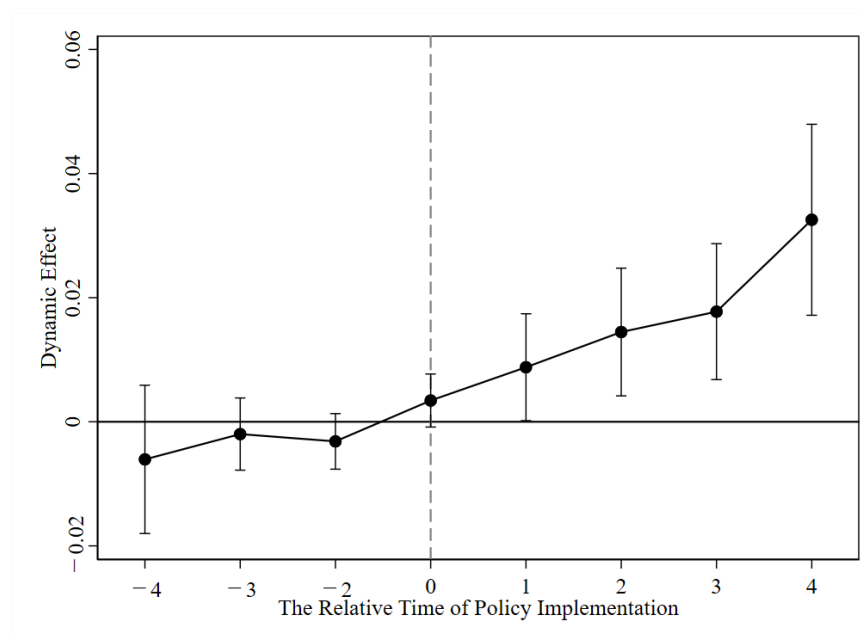


Figure 5. Parallel Trend Test Results.

5.2. Baseline Results

Table 4 reports the estimated effects of the ERUR pilot policy on SEPCR. Column (1) presents the results without control variables or fixed effects. The estimated coefficient of ERUR is positive and statistically significant at the 1% level, providing preliminary evidence for a positive association between ERUR and SEPCR. Column (2) further adds a set of control variables and includes both city and year fixed effects. The baseline coefficient of ERUR is 0.019, statistically significant at the 1% level, indicating that the ERUR policy increases urban SEPCR by approximately 1.9%. This result suggests that ERUR improves both emission reduction efficiency and carbon sequestration capacity through the carbon sequestration effects of ecological restoration and the source-based emission reduction effects of urban repair. Together, these effects support the transition of urban development toward a more sustainable, low-carbon trajectory. Overall, the results substantiate the positive impact of ERUR on SEPCR, supporting Hypothesis 1 and providing a basis for the subsequent mechanism analysis.

In addition, to verify that ERUR has a significant effect on both PRE and CRE, but with a stronger impact on SEPCR, the individual effects of the ERUR pilot policy on both are presented in Columns (3) and (4) of Table 4. In light of these results, the subsequent empirical analysis will focus solely on the relationship between ERUR and SEPCR.

Table 4. Baseline Regression Results.

	(1)	(2)	(3)	(4)
Variables	SEPCR	SEPCR	PRE	CRE
ERUR	0.021 *** (0.006)	0.019 *** (0.006)	0.014 ** (0.007)	0.017 ** (0.007)
lnpgdp		0.033 *** (0.010)	0.026 ** (0.012)	0.034 *** (0.010)
pop		0.000 *** (0.000)	0.000 (0.000)	0.000 *** (0.000)
fin		−0.010 *** (0.003)	−0.003 (0.003)	−0.005 ** (0.003)
gov		0.004	0.006 **	0.005 **

		(0.002)	(0.003)	(0.003)
CS		0.000 ***	0.000	0.000
		(0.000)	(0.000)	(0.000)
Constant	0.497 ***	0.132	−0.006	−0.151
	(0.000)	(0.106)	(0.130)	(0.111)
City effects	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes
N	4794	4794	4794	4794
Adj R-squared	0.908	0.917	0.930	0.856

Note: Robust city-level clustered standard errors are shown in parentheses. The same applies to the following tables. *** and ** indicate significance at the 1%, and 5% levels, respectively.

5.3. Robust Test

5.3.1. Placebo Test

To address concerns about unobserved selection bias and verify that the estimated impacts originate from the ERUR policy itself, this study implements a placebo test by randomly reallocating cities to the treatment and control groups to generate a pseudo policy variable. A total of 500 random shocks are applied to the 282 cities, and counterfactual tests are conducted using the baseline regression model, yielding 500 estimated coefficients. As shown in Figure 6, relative to the actual policy effect, the estimated coefficients obtained from the placebo shocks are concentrated around zero and approximately follow a normal distribution. These coefficients are significantly smaller than the true estimate of 0.019, and most of the associated *p*-values are statistically insignificant. This indicates that the fictitious ERUR policies generated through random assignment do not produce significant effects in the 500 simulations. Therefore, the relationship between ERUR and SEPCR is not significantly influenced by other unobserved factors. The policy effect identified in the baseline regression can thus be attributed to the ERUR policy, and the placebo test is passed.

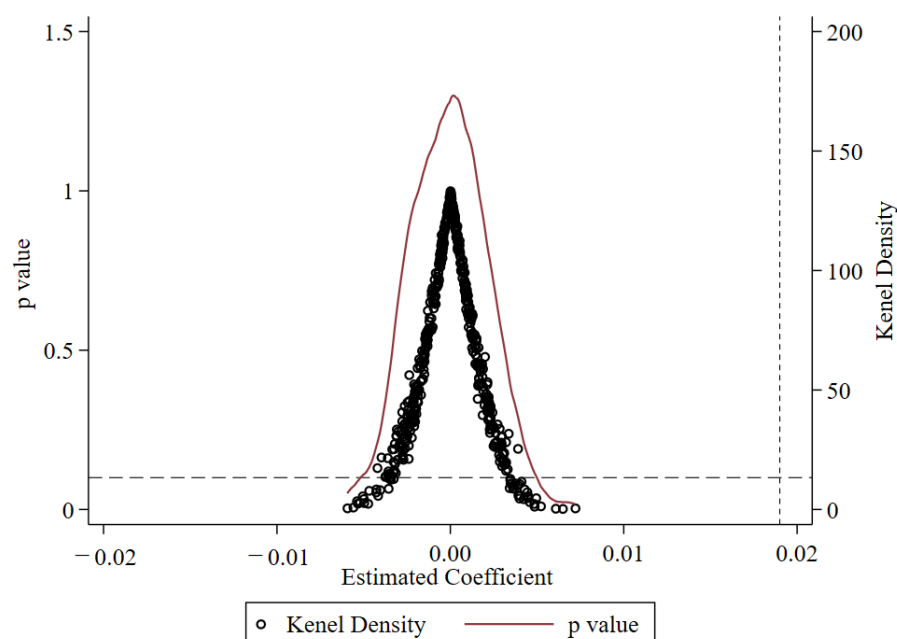


Figure 6. Placebo Test Results.

5.3.2. Stacked Regression Estimator

When identifying policy effects using a multi-period DID model, differences in policy impacts across implementation waves give rise to heterogeneous treatment effects, which could potentially bias the estimated coefficients in the baseline regression. To address this potential bias, we follow Cengiz et al. (2019) and adopt a stacked DID approach [66]. The stacked DID method groups observations based on treatment timing and conducts regressions accordingly, aggregating the resulting estimates with appropriate weights. Specifically, the sample is first partitioned based on the timing of policy implementation. Within each subsample, treated units and clean control units are constructed. The subsamples are then stacked to form a pooled dataset, on which the regression analysis is conducted. Table 5 reports the results of the stacked DID estimations, further supporting the role of the ERUR policy in promoting SEPCR. Figure 7 presents the parallel trend plot reconstructed based on the stacked estimates, suggesting that the baseline results are robust to the potential biases discussed above.

Table 5. Stacked DID Results.

Variables	SEPCR
ERUR	0.017 *** (0.006)
Controls	Yes
City effects	Yes
Year effects	Yes
N	12,648
Adj R-squared	0.914

Note: *** indicates significance at the 1% levels. Robust standard errors in parentheses.

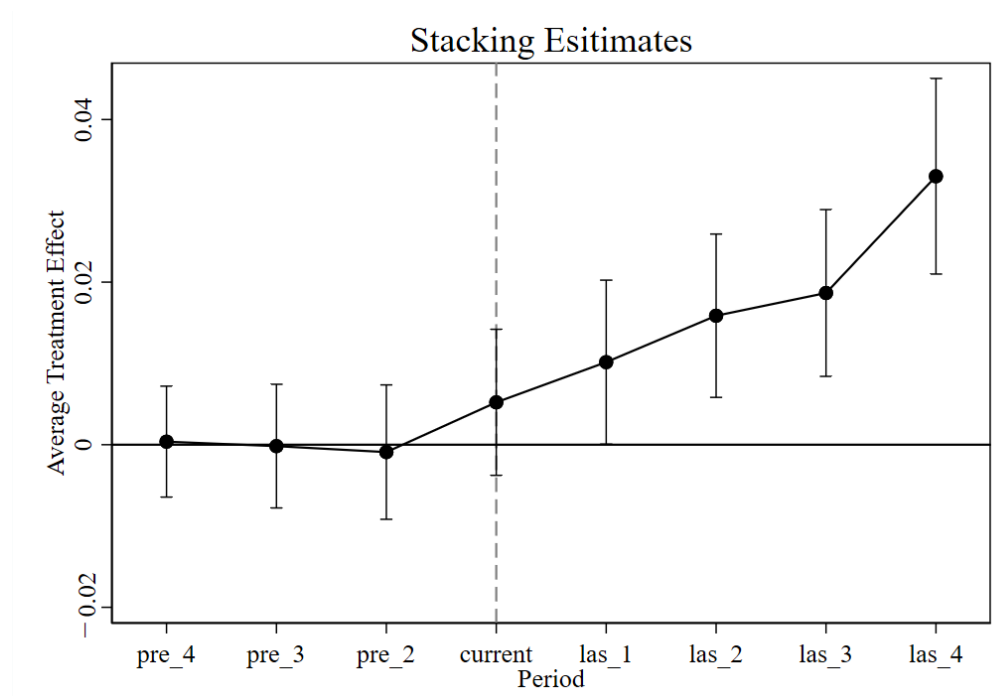


Figure 7. Parallel Trends Based on the Stacked DID Estimator.

5.3.3. Goodman-Bacon Decomposition

When treatment effects are heterogeneous, the two-way fixed-effects model may suffer from biased weighting, potentially distorting the DID estimates. To address this concern, this study applies the Goodman-Bacon decomposition [67] to systematically

decompose the DID estimator and examine its components in detail. By analyzing the relative weights of comparison groups, we assess the extent of potential estimation bias and its contribution to the overall results, as reported in Table 6. As shown in Panel A, the net effect of the ERUR pilot policy on SEPCR, measured by comparing treated cities with control cities, accounts for a dominant share of the total weight, and the sign of the estimated coefficient remains unchanged. In contrast, the comparison component reflecting treatment effect heterogeneity, arising from comparisons between later-treated and earlier-treated groups, accounts for only 0.5% of the total weight. This indicates that heterogeneous treatment effects have a negligible impact on the baseline estimates. Panel B further supports this, showing that valid comparison components account for 97.9% of the total weight. Overall, the Goodman-Bacon decomposition results support the reliability and robustness of the study's main findings.

Table 6. Goodman-Bacon Decomposition Results.

Panel A: Without Control Variables		
DID Comparison	Weight	Average DID Estimates
Earlier T vs. Later C	0.010	−0.001
Later T vs. Earlier C	0.005	−0.007
T vs. Never treated	0.985	0.022
Panel B: With Control Variables		
	Beta	Total Weight
Timing groups	−0.003	0.015
Never timing	0.022	0.979
Within	−0.332	0.006

5.3.4. Anticipation Effect Test

Anticipatory responses to the ERUR policy may lead to different SEPCR trends between the treatment and control groups prior to implementation, potentially complicating the identification of the net effect of the policy pilot on SEPCR. To test for anticipatory effects, this study shifts the ERUR policy implementation by one, two, and three years, respectively, and constructs the corresponding lead policy variables, denoted as ERUR_1, ERUR_2, and ERUR_3. After adding the lead terms to the baseline regression, Table 7 shows that the core coefficient remains significant, whereas the lead variables themselves are insignificant. This suggests that the ERUR policy does not exhibit anticipatory effects on SEPCR, thereby providing further support for the robustness of the parallel trends assumption.

Table 7. Expectation Effect Test.

	(1)	(2)	(3)
Variables	SEPCR	SEPCR	SEPCR
ERUR	0.014 *** (0.004)	0.016 *** (0.004)	0.017 *** (0.005)
ERUR_1	0.006 (0.005)		
ERUR_2		0.004 (0.005)	
ERUR_3			0.003 (0.005)
Constant	0.132 (0.106)	0.132 (0.106)	0.132 (0.106)
Controls	Yes	Yes	Yes

City effects	Yes	Yes	Yes
Year effects	Yes	Yes	Yes
N	4794	4794	4794
Adj R-squared	0.917	0.917	0.917

Note: *** indicates significance at the 1% level. Robust standard errors in parentheses.

5.3.5. PSM-DID

To address potential selection bias in evaluating the ERUR policy, we follow Heckman (1998) and employ a PSM-DID approach as a robustness check [68]. Specifically, all control variables are used as matching covariates. A 1:2 nearest-neighbor matching procedure is conducted annually, after which the multi-period DID model is re-estimated on the matched sample. As reported in Column (2) of Table 8, the estimated coefficient for ERUR remains statistically significant, further supporting the robustness and validity of the baseline regression results.

Table 8. PSM-DID Test.

Variables	PSM-DID
ERUR	0.019 *** (0.006)
Constant	0.154 (0.106)
Controls	Yes
City effects	Yes
Year effects	Yes
N	4691
Adj R-squared	0.920

Note: *** indicates significance at the 1% level. Robust standard errors in parentheses.

5.3.6. Exclusion of Other Policies

To address potential bias from overlapping effects of other pollution- and carbon-related policies during the sample period, three major environmental regulations are individually added to the baseline specification. These include: (a) the Low-Carbon City Pilot (LCCP) policy, implemented since 2010, which seeks to identify pathways for aligning economic development with carbon emission reduction; (b) the Emission Trading Scheme (ETS), launched in 2007, which serves as a market-based mechanism for regulating pollutant emissions; and (c) the Priority Air Pollution Control Zone (PAPCZ) policy, established in 2013, which enhances air pollution control in key regions through targeted regulatory measures. As shown in Table 9, the main results remain robust after accounting for the potential confounding effects of these concurrent policies.

Table 9. Exclusion of Other Policies Results.

	(1)	(2)	(3)	(4)	(5)
Variables	SEPCR	SEPCR	SEPCR	SEPCR	SEPCR
ERUR	0.019 *** (0.006)	0.017 *** (0.006)	0.019 *** (0.006)	0.018 *** (0.006)	0.016 *** (0.006)
LCCP		0.009 ** (0.004)			0.009 ** (0.004)
ETS			0.015 *** (0.005)		0.012 ** (0.005)
PAPCZ				0.012 ** (0.005)	0.011 ** (0.005)

Constant	0.132 (0.106)	0.125 (0.105)	0.128 (0.105)	0.121 (0.104)	0.113 (0.104)
Controls	Yes	Yes	Yes	Yes	Yes
City effects	Yes	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes	Yes
N	4794	4794	4794	4794	4794
Adj R-squared	0.917	0.917	0.917	0.917	0.918

Note: *** and ** indicate significance at the 1%, and 5% levels, respectively. Robust standard errors in parentheses.

5.3.7. Other Robustness Tests

To ensure the reliability of empirical findings, we conduct a series of additional robustness tests. First, to address potential bias from separately measuring PRE and CRE prior to coupling, this study follows Zhu et al. (2023) and uses industrial SO₂ and CO₂ emissions to measure pollution and carbon reduction levels, respectively [69]. These indicators are then coupled to construct an alternative measure of SEPCR. Given that greenhouse gas and air pollutant emissions are undesirable outputs, a lower value of the coupling coordination index indicates a stronger interdependence between pollution and carbon emissions, thereby indicating a higher level of synergistic performance. The corresponding regression results are reported in Column (1) of Table 10. Second, to test the generalizability of the policy effects, this study follows Yu and Hu (2024) and re-estimates the model after excluding China's four centrally administered municipalities, 28 provincial capital cities, and 15 sub-provincial cities, which typically play a leading role in regional development [70]. The estimation results are presented in Column (2) of Table 10. Third, to eliminate potential interference from COVID-19, observations from 2020 are excluded from the sample, with the corresponding results shown in Column (3) of Table 10. Fourth, in constructing SEPCR using the coupling coordination degree model, equal weights are initially assigned to PRE and CRE ($a = b = 0.5$). To assess the sensitivity of the results to alternative weight specifications, the weights are redefined as $(a, b) = (1/3, 2/3)$ and $(2/3, 1/3)$, following Song (2018) [71], with the results shown in Columns (4) and (5) of Table 10. Finally, drawing on Chernozhukov et al. (2018), this study employs a double machine learning (DML) framework for further robustness checks [72]. The sample is randomly split at a 1:3 ratio, and Lasso regression is used for parameter estimation, with the results presented in Column (6) of Table 10. In addition, neural network methods are applied for identification, and the corresponding results are shown in Column (7). Overall, these robustness checks consistently indicate that the ERUR policy exerts a statistically significant and positive effect on SEPCR, in line with the baseline findings.

Table 10. Other Robustness Tests Results.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Outcome Variable Replacement	Exclusion of Central Cities	Exclusion of COVID-19 Interference	$a = 1/3$ $b = 2/3$	$a = 2/3$ $b = 1/3$	Lasso Regression	Neural Network
Variables	SEPCR	SEPCR	SEPCR	SEPCR	SEPCR	SEPCR	SEPCR
ERUR	−0.404 ** (0.190)	0.016 ** (0.006)	0.019 *** (0.006)	0.019 *** (0.006)	0.019 *** (0.006)	0.018 *** (0.003)	0.195 *** (0.057)
Constant	−4.274 ** (2.049)	0.061 (0.115)	0.171 (0.104)	0.102 (0.107)	0.161 (0.105)		
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes

N	4794	4199	4512	4794	4794	4794	4794
Adj R-squared	0.923	0.911	0.917	0.905	0.926		

Note: *** and ** indicate significance at the 1%, and 5% levels, respectively. Robust standard errors in parentheses.

6. Further Analysis

6.1. Heterogeneity Analysis

6.1.1. Geographical Location Heterogeneity

Based on China's regional classification, the full sample is divided into four subsamples—Eastern, Central, Western, and Northeastern regions—and separate regressions are conducted. As reported in Table 11, the ERUR policy exhibits a statistically significant positive effect on SEPCR primarily in the eastern region. Although the estimated coefficients for the central, western, and northeastern regions remain positive, they are not statistically significant, with magnitudes decreasing in the order of Western, Central, and Northeastern China. These regional disparities likely reflect differences in development foundations and factor endowments. The eastern region benefits from stronger economic capacity and technological advantages, which facilitate industrial upgrading toward high value-added and low-pollution sectors, thereby amplifying the SEPCR-enhancing effect of ERUR. In contrast, the central and western regions face constraints stemming from weaker economic bases, limited access to high-end production factors, and the relocation of pollution-intensive industries from the east. These factors increase energy-intensive activities and may weaken policy effectiveness. Notably, the western region displays a relatively larger coefficient than the central region, possibly because ecological restoration generates higher marginal returns in areas with more fragile ecological baselines. By comparison, the northeastern region is characterized by slow industrial restructuring, heavy reliance on energy-intensive industries, and weaker factor agglomeration, which together limit ERUR's capacity to enhance SEPCR.

Table 11. Geographical Location Heterogeneity Results.

	(1)	(2)	(3)	(4)
Variables	Eastern	Central	Western	Northeastern
ERUR	0.021 *** (0.008)	0.008 (0.012)	0.017 (0.011)	0.003 (0.010)
Constant	−0.063 (0.174)	0.528 *** (0.159)	0.036 (0.251)	−0.933 *** (0.313)
Controls	Yes	Yes	Yes	Yes
City effects	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes
N	1462	1360	1411	561
Adj R-squared	0.948	0.927	0.907	0.900

Note: *** indicates significance at the 1% level. Robust standard errors in parentheses.

6.1.2. Resource Endowment Heterogeneity

Following Tang et al. (2025), the 282 cities are further classified into resource-based and non-resource-based cities, followed by group-specific regression analysis [13]. Table 12 indicates that the ERUR policy significantly improves SEPCR in non-resource-based cities, whereas it has no significant effect in resource-based cities. This heterogeneity primarily reflects differences in industrial path dependence. Non-resource-based cities are less constrained by resource-dependent industrial structures, enabling the ERUR policy to enhance SEPCR through strengthened environmental and spatial constraints that

accelerate the exit or relocation of pollution-intensive firms, as well as through improved urban amenities that attract capital and technology and facilitate the adoption of green technologies. Conversely, resource-based cities are heavily reliant on industries centered around mineral resources. In these cities, ERUR mainly raises operating costs for incumbent firms but has limited capacity to induce rapid adjustments in industrial composition or energy structures. Moreover, ecological restoration efforts often concentrate on remediating extraction-damaged areas, providing only limited support for SEPCR. As a result, the overall policy effect in resource-based cities remains weak.

Table 12. Resource Endowment Heterogeneity Results.

	(1)	(2)
	Resource-Based	Non-Resource-Based
ERUR	0.006 (0.006)	0.019 *** (0.005)
Constant	0.030 (0.129)	0.238 *** (0.090)
Controls	Yes	Yes
City effects	Yes	Yes
Year effects	Yes	Yes
N	1938	2856
Adj R-squared	0.906	0.934

Note: *** indicates significance at the 1% level. Robust standard errors in parentheses.

6.1.3. Industrial Characteristic Heterogeneity

To examine urban industrial heterogeneity, the sample is divided into old industrial base cities and non-old industrial base cities based on the National Plan for the Adjustment and Renovation of Old Industrial Bases (2013–2022) [30]. Table 13 indicates that the ERUR policy has no significant effect on SEPCR in old industrial base cities, while it has a statistically significant positive effect in non-old industrial base cities. This heterogeneity primarily reflects differences in historical industrial structures and development trajectories. Old industrial base cities are dominated by heavy industry and traditional manufacturing, characterized by high energy consumption, emissions, and strong path dependence and resource curse effects. High sunk costs, employment inflexibilities, and technological limitations in these cities impede industrial transformation, making it difficult for ERUR to prompt swift adjustments in industrial and energy systems. In contrast, cities outside old industrial bases tend to have more diversified industrial structures, with lower reliance on heavy industries and higher shares of tertiary and high-tech sectors. This flexibility enhances their ability to adopt green policies and technologies, enabling ERUR to more effectively promote industrial and energy optimization and support low-carbon development pathways.

Table 13. Industrial Characteristic Heterogeneity Results.

	(1)	(2)
	Old Industrial Base Cities	Non-Old Industrial Base
ERUR	0.001 (0.008)	0.033 *** (0.008)
Constant	−0.016 (0.165)	0.103 (0.146)
Controls	Yes	Yes
City effects	Yes	Yes

Year effects	Yes	Yes
N	2142	2652
Adj R-squared	0.924	0.924

Note: *** indicates significance at the 1% level. Robust standard errors in parentheses.

6.1.4. Spatial Form Heterogeneity

Urban sprawl is a typical spatial expansion pattern in the process of urbanization, characterized by disorderly outward expansion of built-up areas toward urban peripheries in a low-density, dispersed manner [73]. To examine the heterogeneous effects of urban spatial form on SEPCR, we adopt the urban sprawl index constructed by Wang and Wang (2023) [74], as specified in Equation (6). Based on this index, ERUR pilot cities are classified into high-intensity urban sprawl and low-intensity urban sprawl groups for separate regression analysis. In this index, A_{it} and A_{il} denote the built-up area of city i in year t and in the baseline year (2006), respectively. P_{it} and P_{il} represent the corresponding population sizes in the respective years.

$$Sprawl = \frac{A_{it}/A_{il}}{P_{it}/P_{il}} \quad (6)$$

Table 14 reveals that cities with low-intensity urban sprawl exhibit significantly stronger effects in SEPCR, whereas cities with high-intensity sprawl display insignificant synergistic effects. In low-sprawl cities, compact and orderly spatial structures facilitate integrated environmental governance. Reduced commuting distances increase the feasibility of low-carbon mobility options, which in turn lowers fossil energy use and curbs carbon emissions and air pollutant generation at the source. At the same time, the establishment of urban growth boundaries protects ecological land, such as green spaces and wetlands, thereby enhancing their functions in carbon sequestration and pollutant removal. Moderate population and industrial agglomeration further enhance the efficiency of public infrastructure, including sewage treatment and district heating, through economies of scale, thus lowering energy consumption and governance costs. Together, these mechanisms foster a positive feedback loop of source control, ecological enhancement, and efficient governance, resulting in stronger synergistic effects. In contrast, high-intensity urban sprawl generates systemic inefficiencies through disorderly expansion. Low-density spatial patterns exacerbate job–housing separation and dependence on motorized commuting, leading to higher energy use, carbon emissions, and exhaust pollution. Meanwhile, the expansion of built-up areas erodes ecological regulation functions and increases both governance costs and coordination complexity. As a result, emission growth tends to outweigh governance gains, making it difficult to achieve SEPCR in cities characterized by high-intensity urban sprawl.

Table 14. Spatial Form Heterogeneity Results.

	(1)	(2)
	High-Intensity Urban Sprawl	Low-Intensity Urban Sprawl
ERUR	0.012 (0.008)	0.024 *** (0.007)
Constant	0.041 (0.141)	0.233 (0.141)
Controls	Yes	Yes
City effects	Yes	Yes
Year effects	Yes	Yes
N	2294	2500
Adj R-squared	0.908	0.926

Note: *** indicates significance at the 1% level. Robust standard errors in parentheses.

Figure 8 presents the results of four heterogeneity analyses. In each panel, markers indicate subgroup-specific estimates, and horizontal bars depict confidence intervals. Statistical significance is indicated when the confidence interval does not include zero.

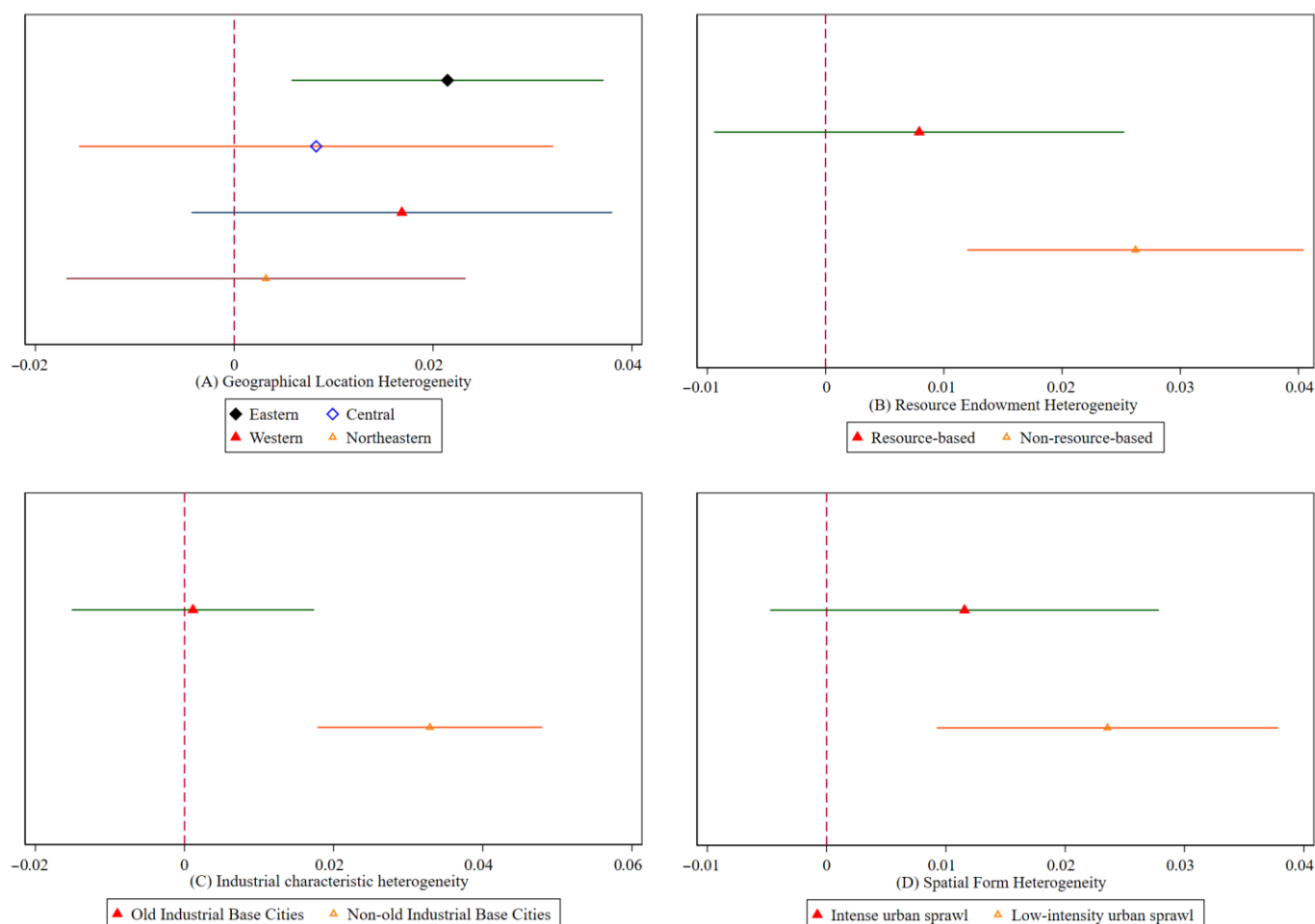


Figure 8. Heterogeneity Analysis Results.

6.2. Mechanism Analysis

This study establishes the following models to systematically examine the impact mechanism of the ERUR policy on SEPCR:

$$Mechanism_{it} = \alpha_2 + \beta_2 ERUR_{it} + \theta_2 X_{it} + \mu_i + \delta_t + \varepsilon_{it} \quad (7)$$

$$SEPCR_{it} = \alpha_3 + \beta_3 ERUR_{it} + \gamma_3 Mechanism_{it} + \theta_3 X_{it} + \mu_i + \delta_t + \varepsilon_{it} \quad (8)$$

where $Mechanism_{it}$ denotes the mechanism variable, and the other variables are defined as explained earlier. As reported in Table 15, the theoretical mechanism analysis indicates that the ERUR policy influences SEPCR primarily through three main channels: economies of scale (ED), industrial structure upgrading (ind), and energy intensity improvement (energy). The ERUR coefficient in Column (2) shows that the policy promotes economic scale expansion by attracting capital, technology, and talent, while improving resource allocation efficiency. These effects unlock economies of scale and improve the effectiveness of centralized environmental governance, thereby strengthening SEPCR. Accordingly, Hypothesis 2 is supported. The results in Column (4) show that the ERUR

policy generates implicit environmental regulation through ecological restoration and urban spatial optimization. These effects compel firms to adjust production processes and factor allocation, accelerate green industrial transformation, and thus improve SEPCR. Thus, Hypothesis 3 is confirmed. Similarly, the ERUR coefficient in Column (6) shows that the policy accelerates the shift from carbon-heavy to clean energy sources. This transition results in a cleaner energy mix, reduces energy intensity, and mitigates CO₂ and air pollutant emissions, reinforcing SEPCR. Therefore, Hypothesis 4 is validated.

Table 15. Mechanism Tests.

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	ED	SEPCR	Ind	SEPCR	Energy	SEPCR
ED		0.062 *** (0.018)				
ind				0.056 *** (0.017)		
energy						−0.024 *** (0.002)
ERUR	0.053 *** (0.018)	0.016 *** (0.005)	0.027 * (0.014)	0.018 *** (0.006)	−0.436 *** (0.085)	0.009 * (0.005)
Constant	−0.595 (0.587)	0.169 * (0.095)	4.590 *** (0.230)	−0.124 (0.125)	5.761 *** (1.971)	0.270 *** (0.078)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
City effects	Yes	Yes	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes	Yes	Yes
N	4794	4794	4794	4794	4794	4794
Adj R-squared	0.995	0.919	0.838	0.918	0.714	0.945

Note: *** and * indicate significance at the 1%, and 10% levels, respectively. Robust standard errors in parentheses.

7. Discussion and Conclusions

At a critical stage of China’s transition to greener, decarbonized development, urban regeneration initiatives have become key policy tools for promoting high-quality urban growth and achieving SEPCR. Using panel data for 282 prefecture-level-and-above cities from 2006 to 2022, this study exploits the ERUR pilot as an exogenous policy shock and applies a multi-period DID framework to identify its impact on SEPCR. The results show that the ERUR policy significantly increases SEPCR by approximately 1.9%. Heterogeneity analyses reveal that the effects vary by geography, resource endowments, industrial characteristics, and spatial form, with stronger impacts in the eastern regions, non-resource-based cities, non-old industrial base cities, and cities with lower urban sprawl. Mechanism analyses further show that ERUR enhances SEPCR primarily by leveraging economies of scale, promoting industrial structure upgrading, and reducing energy intensity. Overall, these findings provide robust empirical evidence for refining urban regeneration policies, advancing differentiated pollution–carbon governance strategies, and promoting sustainable urban development and ecological civilization.

The findings generate several key policy implications. First, the top-level incentive framework for collaborative governance should be restructured to correct distorted incentives and mitigate spatial competition. Under fiscal decentralization and promotion tournament systems, local governments often prioritize economic growth and fiscal revenue, which encourages regulatory relaxation and “race-to-the-bottom” dynamics and complicates the integration of SEPCR into performance evaluation. Excessive focus on short-term performance may intensify intergovernmental competition, leading to campaign-style

emission reductions, carbon leakage, and pollution haven effects [32,38]. Therefore, a cost-effective and responsibility-oriented governance framework is essential. This includes establishing regional environmental cooperation mechanisms with harmonized regulatory standards, improving cross-regional compensation and fiscal transfer schemes, and integrating SEPCR as a core criterion in official evaluations. Strengthening environmental enforcement will help transform spatial spillovers from zero-sum competition into cooperative outcomes. Second, ERUR policies should be better aligned with urban characteristics through differentiated and adaptive design. Given substantial heterogeneity in resource endowments, development stages, and institutional capacity, the effectiveness of ERUR policies varies considerably across cities. Eastern regions generally benefit from stronger legal frameworks and greater fiscal and technological capacity, whereas many cities in central, western, and old industrial regions face constraints related to regulatory capacity and institutional flexibility. A “one-city-one-policy” approach is essential. Cities should be classified according to functional zoning and supported through region-specific strategies, with eastern cities focusing on technological and industrial upgrading, and other regions prioritizing digital infrastructure development, talent attraction, and employment-supporting policies. Dynamic feedback mechanisms, including policy simulation and early-warning systems, should also be established to enhance adaptability. Third, the institutional foundations of SEPCR under ERUR policies should be strengthened by improving supporting systems along key transmission channels. Policy efforts should focus on economic scale effects, industrial upgrading, and energy intensity improvement. This requires increased investment in green R&D, the use of fiscal and tax instruments to guide firms toward greener production, the accelerated deployment of clean energy technologies and intelligent monitoring systems, and enhanced collaborative innovation and talent-support mechanisms to sustain long-term SEPCR improvements.

This study advances the literature on urban environmental governance by examining the environmental and climate effects of urban regeneration from a spatial governance perspective. Unlike prior research that focuses on isolated environmental regulations or specific technological pathways, it situates urban regeneration within a broader spatial governance framework and evaluates its role in promoting SEPCR. This approach responds to recent international calls to integrate spatial planning and transitional governance into sustainability analyses, while addressing the limited empirical evidence on the environmental impacts of spatial policies. The findings clarify the mechanisms through which urban regeneration influences SEPCR, showing that ERUR policies operate primarily through economies of scale, industrial structure upgrading, and energy intensity improvement. These results illustrate how spatial interventions can reshape production organization, factor allocation, and energy use. Moreover, significant heterogeneity across regions, resource endowments, industrial characteristics, and spatial forms highlights the context-dependent nature of policy effectiveness, emphasizing the importance of place-based sustainability strategies over one-size-fits-all policies. Beyond China, the ERUR experience shows how urban regeneration can be integrated with environmental regulation and climate mitigation through a pilot-based, incremental approach. Such modular policy designs—combining spatial planning, environmental governance, and economic restructuring—provide a flexible reference for cities globally pursuing low-carbon and sustainable development under varying institutional conditions.

Nevertheless, several limitations remain that require further examination. First, due to data availability and consistency constraints, this study utilizes panel data for cities from 2006 to 2022. Micro-level data from counties and firms are not included, which means that the mechanism analysis relies mainly on macro-level correlations and inferences, lacking direct verification of micro-level transmission channels. Due to data time constraints, it is difficult to fully assess the long-term sustainability of the policy effects.

Future research could conduct multi-scale longitudinal case studies, focusing on key enterprises within urban regeneration districts to analyze the evolution of industrial structures during the regeneration process, and integrate these findings with macro-level effects. Expanding the temporal scope of the data would also enrich and improve research conclusions in this field. Second, this study uses the ERUR policy as a proxy for urban regeneration to examine its impact on SEPCR. Although ERUR is a comprehensive initiative, urban regeneration is inherently multidimensional, involving spatial restructuring, functional upgrading, and social inclusion, which may not be fully captured by a single-policy perspective. Future research could broaden the scope by incorporating multiple policy instruments to evaluate governance performance more comprehensively. Finally, as the analysis is based on data from Chinese cities, the findings and policy implications are shaped by China's institutional context. Extending this framework to countries or regions with different institutional settings through cross-context comparisons would assess the external validity of the conclusions.

Author Contributions: Conceptualization, T.L. and H.Y.; methodology, H.Y.; software, H.Y.; validation, H.Y.; formal analysis, K.Z.; investigation, C.C.; data curation, H.Y.; writing—original draft preparation, H.Y.; writing—review and editing, T.L.; visualization, K.Z.; supervision, T.L.; project administration, T.L.; funding acquisition, T.L. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the project “Effect, Transmission Mechanism and Regulation Strategy of Interface Breakthrough in China–ASEAN Cross-border Economic Cooperation Zone”, supported by the National Natural Science Foundation of China (Regional Fund Project), Approval No. 42161030.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data presented in this study are available upon request from the corresponding author.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Chen, Y.; Yao, Z.; Zhong, K. Do Environmental Regulations of Carbon Emissions and Air Pollution Foster Green Technology Innovation: Evidence from China's Prefecture-Level Cities. *J. Clean. Prod.* **2022**, *350*, 131537. <https://doi.org/10.1016/j.jclepro.2022.131537>.
2. Li, X.; Qiao, Y.; Shi, L. The Aggregate Effect of Air Pollution Regulation on CO₂ Mitigation in China's Manufacturing Industry: An Econometric Analysis. *J. Clean. Prod.* **2017**, *142*, 976–984. <https://doi.org/10.1016/j.jclepro.2016.03.015>.
3. Unger, N. Global Climate Forcing by Criteria Air Pollutants. *Annu. Rev. Environ. Resour.* **2012**, *37*, 1–24. <https://doi.org/10.1146/annurev-environ-082310-100824>.
4. Ayres, R.U.; Walter, J. The Greenhouse Effect: Damages, Costs and Abatement. *Environ. Resour. Econ.* **1991**, *1*, 237–270. <https://doi.org/10.1007/BF00367920>.
5. Li, Z.; Bai, T.; Tang, C. How Does the Low-Carbon City Pilot Policy Affect the Synergistic Governance Efficiency of Carbon and Smog? Quasi-Experimental Evidence from China. *J. Clean. Prod.* **2022**, *373*, 133809. <https://doi.org/10.1016/j.jclepro.2022.133809>.
6. Yu, X.; Wu, Z.; Zheng, H.; Li, M.; Tan, T. How Urban Agglomeration Improve the Emission Efficiency? A Spatial Econometric Analysis of the Yangtze River Delta Urban Agglomeration in China. *J. Environ. Manag.* **2020**, *260*, 110061. <https://doi.org/10.1016/j.jenvman.2019.110061>.
7. Makido, Y.; Dhakal, S.; Yamagata, Y. Relationship between Urban Form and CO₂ Emissions: Evidence from Fifty Japanese Cities. *Urban Clim.* **2012**, *2*, 55–67. <https://doi.org/10.1016/j.uclim.2012.10.006>.

8. de Jong, M.; Joss, S.; Schraven, D.; Zhan, C.; Weijnen, M. Sustainable–Smart–Resilient–Low Carbon–Eco–Knowledge Cities; Making Sense of a Multitude of Concepts Promoting Sustainable Urbanization. *J. Clean. Prod.* **2015**, *109*, 25–38. <https://doi.org/10.1016/j.jclepro.2015.02.004>.
9. Zhao, T.; Zhu, J.; Jian, Z.; Zhou, X.; Zhang, P. Effects of the “Urban Double Repairs” Policy on Urban Land-Use Carbon Emission Efficiency. *Sustainability* **2024**, *16*, 10531. <https://doi.org/10.3390/su162310531>.
10. Jia, R.; Fan, M.; Shao, S.; Yu, Y. Urbanization and Haze-Governance Performance: Evidence from China’s 248 Cities. *J. Environ. Manag.* **2021**, *288*, 112436. <https://doi.org/10.1016/j.jenvman.2021.112436>.
11. Zhang, H.; Li, S. Carbon Emissions’ Spatial-Temporal Heterogeneity and Identification from Rural Energy Consumption in China. *J. Environ. Manag.* **2022**, *304*, 114286. <https://doi.org/10.1016/j.jenvman.2021.114286>.
12. Dong, Z.; Xia, C.; Fang, K.; Zhang, W. Effect of the Carbon Emissions Trading Policy on the Co-Benefits of Carbon Emissions Reduction and Air Pollution Control. *Energy Policy* **2022**, *165*, 112998. <https://doi.org/10.1016/j.enpol.2022.112998>.
13. Tang, Y.; Hu, Y.; Cui, A. Research on the Synergistic Effects of Market-Oriented Environmental Regulations on Pollution and Carbon Emission Reduction. *J. Environ. Manag.* **2025**, *380*, 125115. <https://doi.org/10.1016/j.jenvman.2025.125115>.
14. Cai, S.; Ma, Q.; Wang, S.; Zhao, B.; Brauer, M.; Cohen, A.; Martin, R.V.; Zhang, Q.; Li, Q.; Wang, Y.; et al. Impact of Air Pollution Control Policies on Future PM_{2.5} Concentrations and Their Source Contributions in China. *J. Environ. Manag.* **2018**, *227*, 124–133. <https://doi.org/10.1016/j.jenvman.2018.08.052>.
15. Yan, Y.; Zhang, X.; Zhang, J.; Li, K. Emissions Trading System (ETS) Implementation and Its Collaborative Governance Effects on Air Pollution: The China Story. *Energy Policy* **2020**, *138*, 111282. <https://doi.org/10.1016/j.enpol.2020.111282>.
16. Yao, X.; Kou, D.; Shao, S.; Li, X.; Wang, W.; Zhang, C. Can Urbanization Process and Carbon Emission Abatement Be Harmonious? New Evidence from China. *Environ. Impact Assess. Rev.* **2018**, *71*, 70–83. <https://doi.org/10.1016/j.eiar.2018.04.005>.
17. Liu, L.; Chen, M.; Wang, H.; Liu, B. How Does the Chinese Pilot Policy on Information Consumption Affect Carbon Emissions? *Sustain. Prod. Consum.* **2023**, *41*, 88–106. <https://doi.org/10.1016/j.spc.2023.07.030>.
18. Zhou, W.; Zhang, Y.; Li, X. Artificial Intelligence, Green Technological Progress, Energy Conservation, and Carbon Emission Reduction in China: An Examination Based on Dynamic Spatial Durbin Modeling. *J. Clean. Prod.* **2024**, *446*, 141142. <https://doi.org/10.1016/j.jclepro.2024.141142>.
19. Galeotti, M.; Lanza, A. Richer and Cleaner? A Study on Carbon Dioxide Emissions in Developing Countries. *Energy Policy* **1999**, *27*, 565–573. [https://doi.org/10.1016/S0301-4215\(99\)00047-6](https://doi.org/10.1016/S0301-4215(99)00047-6).
20. Kaufmann, R.K.; Davidsdottir, B.; Garnham, S.; Pauly, P. The Determinants of Atmospheric SO₂ Concentrations: Reconsidering the Environmental Kuznets Curve. *Ecol. Econ.* **1998**, *25*, 209–220. [https://doi.org/10.1016/S0921-8009\(97\)00181-X](https://doi.org/10.1016/S0921-8009(97)00181-X).
21. Liu, Y.-S.; Cao, Y.; Hou, J.-J.; Zhang, J.-T.; Yang, Y.-O.; Liu, L.-C. Identifying Common Paths of CO₂ and Air Pollutants Emissions in China. *J. Clean. Prod.* **2020**, *256*, 120599. <https://doi.org/10.1016/j.jclepro.2020.120599>.
22. Wang, B.; Wang, Y.; Zhao, Y. Collaborative Governance Mechanism of Climate Change and Air Pollution: Evidence from China. *Sustainability* **2021**, *13*, 6785. <https://doi.org/10.3390/su13126785>.
23. Zheng, B.; Tong, D.; Li, M.; Liu, F.; Hong, C.; Geng, G.; Li, H.; Li, X.; Peng, L.; Qi, J.; et al. Trends in China’s Anthropogenic Emissions Since 2010 as the Consequence of Clean Air Actions. *Atmos. Chem. Phys.* **2018**, *18*, 14095–14111. <https://doi.org/10.5194/acp-18-14095-2018>.
24. Guan, Y.; Xiao, Y.; Li, B. Spatial–Temporal Evolution, Drivers, and Pathways of the Synergistic Effects of Digital Transformation on Pollution and Carbon Reduction in Heavily Polluting Enterprises. *Stoch. Environ. Res. Risk Assess.* **2024**, *38*, 2693–2709. <https://doi.org/10.1007/s00477-024-02705-3>.
25. Mai, W.; Xiong, L.; Liu, B. Measuring the Synergy of Air Pollution and CO₂ Emission in Chinese Urban Agglomerations: An Evaluation from the Aggregate Impact and Correlation Perspectives. *Sci. Rep.* **2025**, *15*, 11963. <https://doi.org/10.1038/s41598-025-96834-6>.
26. Yi, H.; Zhao, L.; Qian, Y.; Zhou, L.; Yang, P. How to Achieve Synergy Between Carbon Dioxide Mitigation and Air Pollution Control? Evidence from China. *Sustain. Cities Soc.* **2022**, *78*, 103609. <https://doi.org/10.1016/j.scs.2021.103609>.
27. Bai, T.; Qi, Y.; Li, Z.; Xu, D. Will Carbon Emission Trading Policy Improve the Synergistic Reduction Efficiency of Pollution and Carbon? Evidence from 216 Chinese Cities. *Manag. Decis. Econ.* **2025**, *46*, 2120–2143. <https://doi.org/10.1002/mde.4014>.
28. Chen, S.; Tan, Z.; Mu, S.; Wang, J.; Chen, Y.; He, X. Synergy Level of Pollution and Carbon Reduction in the Yangtze River Economic Belt: Spatial-Temporal Evolution Characteristics and Driving Factors. *Sustain. Cities Soc.* **2023**, *98*, 104859. <https://doi.org/10.1016/j.scs.2023.104859>.
29. Alvarez-Herranz, A.; Balsalobre-Lorente, D.; Shahbaz, M.; Cantos, J.M. Energy Innovation and Renewable Energy Consumption in the Correction of Air Pollution Levels. *Energy Policy* **2017**, *105*, 386–397. <https://doi.org/10.1016/j.enpol.2017.03.009>.

30. Hu, J. Synergistic Effect of Pollution Reduction and Carbon Emission Mitigation in the Digital Economy. *J. Environ. Manag.* **2023**, *337*, 117755. <https://doi.org/10.1016/j.jenvman.2023.117755>.
31. Yin, Q.; Huang, Y.; Ding, C.; Jing, X. Towards Sustainable Development: Can Green Digital Finance Become an Accelerator for Reducing Pollution and Carbon Emissions in China? *Sustain. Cities Soc.* **2024**, *114*, 105722. <https://doi.org/10.1016/j.scs.2024.105722>.
32. Cao, Y.; Wu, Y.; Li, Z.; Wang, Q. Climate Policy and Carbon Leakage: Evidence from the Low-Carbon City Pilot Program in China. *Environ. Impact Assess. Rev.* **2025**, *110*, 107730. <https://doi.org/10.1016/j.eiar.2024.107730>.
33. Xian, B.; Wang, Y.; Xu, Y.; Wang, J.; Li, X. Assessment of the Co-Benefits of China's Carbon Trading Policy on Carbon Emissions Reduction and Air Pollution Control in Multiple Sectors. *Econ. Anal. Policy* **2024**, *81*, 1322–1335. <https://doi.org/10.1016/j.eap.2024.01.011>.
34. Wang, Z.; Yu, L.; Zheng, M.; Xing, Y.; Liu, X.; Wang, Y.; Xiao, Z. One Fee, Two Reductions: The Double Abatement Effect of Pollutant Discharge Fees on Industrial Pollution and Carbon Emissions. *Front. Environ. Sci.* **2022**, *10*, 928434. <https://doi.org/10.3389/fenvs.2022.928434>.
35. Zhang, X.; Yan, T.; Zhang, S.; Zhang, Z.; Feng, Y. Assessing the Synergy Reduction Effects of the Renewable Energy Policies on Environmental Pollution and Carbon Emissions in China. *Int. Rev. Financ. Anal.* **2025**, *105*, 104421. <https://doi.org/10.1016/j.irfa.2025.104421>.
36. Su, P.; Cong, X.; Wang, L.; Šaparauskas, J.; Ustinovičius, L.; Skibniewski, M.J. Spatial Network Characteristics and Influencing Factors of the Synergistic Effects of Pollution Reduction and Carbon Emission Reduction in “Zero Waste City” Clusters. *J. Clean. Prod.* **2025**, *493*, 144924. <https://doi.org/10.1016/j.jclepro.2025.144924>.
37. Chen, S.; Tan, Z.; Wang, J.; Zhang, L.; He, X.; Mu, S. Spatial and Temporal Evolution of Synergizing the Reduction of Pollution and Carbon Emissions and Examination on Comprehensive Pilot Effects—Evidence from the National Eco-Industrial Demonstration Parks in China. *Environ. Impact Assess. Rev.* **2023**, *101*, 107147. <https://doi.org/10.1016/j.eiar.2023.107147>.
38. Zhang, W.; Li, G.; Uddin, M.K.; Guo, S. Environmental Regulation, Foreign Investment Behavior, and Carbon Emissions for 30 Provinces in China. *J. Clean. Prod.* **2020**, *248*, 119208. <https://doi.org/10.1016/j.jclepro.2019.119208>.
39. Seabrook, L.; Mcalpine, C.A.; Bowen, M.E. Restore, Repair or Reinvent: Options for Sustainable Landscapes in a Changing Climate. *Landsc. Urban Plan.* **2011**, *100*, 407–410. <https://doi.org/10.1016/j.landurbplan.2011.02.015>.
40. Cao, K.; Deng, Y.; Song, C. Exploring the Drivers of Urban Renewal through Comparative Modeling of Multiple Types in Shenzhen, China. *Cities* **2023**, *137*, 104294. <https://doi.org/10.1016/j.cities.2023.104294>.
41. Wang, H.; Shen, Q.; Tang, B.-S.; Lu, C.; Peng, Y.; Tang, L.-Y. A Framework of Decision-Making Factors and Supporting Information for Facilitating Sustainable Site Planning in Urban Renewal Projects. *Cities* **2014**, *40*, 44–55. <https://doi.org/10.1016/j.cities.2014.04.005>.
42. Haase, D.; Kabisch, S.; Haase, A.; Andersson, E.; Banzhaf, E.; Baró, F.; Brenck, M.; Fischer, L.K.; Frantzeskaki, N.; Kabisch, N.; et al. Greening Cities—To Be Socially Inclusive? About the Alleged Paradox of Society and Ecology in Cities. *Habitat Int.* **2017**, *64*, 41–48. <https://doi.org/10.1016/j.habitatint.2017.04.005>.
43. Jiang, J.; Zhang, H.; Huang, Q.; Liu, F.; Li, L.; Qiu, H.; Zhou, S. Diagnosis of Key Ecological Restoration Areas in Territorial Space under the Guidance of Resilience: A Case Study of the Chengdu–Chongqing Region. *Land* **2023**, *12*, 973. <https://doi.org/10.3390/land12050973>.
44. Jiang, F.; Li, J.; Ma, L.; Dong, Z.; Chen, W.; Broyd, T.; Wang, G. Sustainable Urban Road Planning under the Digital Twin-MCDM-GIS Framework Considering Multidisciplinary Factors. *J. Clean. Prod.* **2024**, *469*, 143097. <https://doi.org/10.1016/j.jclepro.2024.143097>.
45. Wang, M.; Zhang, F.; Wu, F. Governing Urban Redevelopment: A Case Study of Yongqingfang in Guangzhou, China. *Cities* **2022**, *120*, 103420. <https://doi.org/10.1016/j.cities.2021.103420>.
46. Li, Z.; Ning, K.; Chen, J.; Liu, C.; Wang, D.; Nie, X.; Hu, X.; Wang, L.; Wang, T. Soil and Water Conservation Effects Driven by the Implementation of Ecological Restoration Projects: Evidence from the Red Soil Hilly Region of China in the Last Three Decades. *J. Clean. Prod.* **2020**, *260*, 121109. <https://doi.org/10.1016/j.jclepro.2020.121109>.
47. Zhang, W.; Xu, D. Benefits Evaluation of Ecological Restoration Projects Based on Value Realization of Ecological Products. *J. Environ. Manag.* **2024**, *352*, 120139. <https://doi.org/10.1016/j.jenvman.2024.120139>.
48. Zhang, M.; Hu, P.; Liu, J. The Carbon Tug-of-War: Assessing Dongjiang Waterfront's Carbon Neutrality Potential in the Battle Between Emissions and Sinks. *Ecol. Indic.* **2025**, *174*, 113481. <https://doi.org/10.1016/j.ecolind.2025.113481>.
49. Li, Y.; Zhao, R.; Liu, T.; Zhao, J. Does Urbanization Lead to More Direct and Indirect Household Carbon Dioxide Emissions? Evidence from China during 1996–2012. *J. Clean. Prod.* **2015**, *102*, 103–114. <https://doi.org/10.1016/j.jclepro.2015.04.037>.

50. Fan, J.-S.; Zhou, L. Impact of Urbanization and Real Estate Investment on Carbon Emissions: Evidence from China's Provincial Regions. *J. Clean. Prod.* **2019**, *209*, 309–323. <https://doi.org/10.1016/j.jclepro.2018.10.201>.
51. Zhang, N.; Yu, K.; Chen, Z. How Does Urbanization Affect Carbon Dioxide Emissions? A Cross-Country Panel Data Analysis. *Energy Policy* **2017**, *107*, 678–687. <https://doi.org/10.1016/j.enpol.2017.03.072>.
52. Sadorsky, P. The Effect of Urbanization on CO₂ Emissions in Emerging Economies. *Energy Econ.* **2014**, *41*, 147–153. <https://doi.org/10.1016/j.eneco.2013.11.007>.
53. Lorente, D.B.; Álvarez-Herranz, A. Economic Growth and Energy Regulation in the Environmental Kuznets Curve. *Environ. Sci. Pollut. Res.* **2016**, *23*, 16478–16494. <https://doi.org/10.1007/s11356-016-6773-3>.
54. Cao, Y.; Ren, W.; Yue, L. Environmental Regulation and Carbon Emissions: New Mechanisms in Game Theory. *Cities* **2024**, *149*, 104945. <https://doi.org/10.1016/j.cities.2024.104945>.
55. Li, M.; Li, Q.; Wang, Y.; Chen, W. Spatial Path and Determinants of Carbon Transfer in the Process of Inter Provincial Industrial Transfer in China. *Environ. Impact Assess. Rev.* **2022**, *95*, 106810. <https://doi.org/10.1016/j.eiar.2022.106810>.
56. Feng, T.; Du, H.; Lin, Z.; Zuo, J. Spatial Spillover Effects of Environmental Regulations on Air Pollution: Evidence from Urban Agglomerations in China. *J. Environ. Manag.* **2020**, *272*, 110998. <https://doi.org/10.1016/j.jenvman.2020.110998>.
57. Jia, H.; Appolloni, A.; Wang, Y. Green Travel: Exploring the Characteristics and Behavior Transformation of Urban Residents in China. *Sustainability* **2017**, *9*, 1043. <https://doi.org/10.3390/su9061043>.
58. Wang, H.; Li, Y.; Lin, W.; Wei, W. How Does Digital Technology Promote Carbon Emission Reduction? Empirical Evidence Based on E-Commerce Pilot City Policy in China. *J. Environ. Manag.* **2023**, *325*, 116524. <https://doi.org/10.1016/j.jenvman.2022.116524>.
59. Zhou, K.; Yang, J.; Yang, T.; Ding, T. Spatial and Temporal Evolution Characteristics and Spillover Effects of China's Regional Carbon Emissions. *J. Environ. Manag.* **2023**, *325*, 116423. <https://doi.org/10.1016/j.jenvman.2022.116423>.
60. Xiao, H.; Ma, Z.; Mi, Z.; Kelsey, J.; Zheng, J.; Yin, W.; Yan, M. Spatio-Temporal Simulation of Energy Consumption in China's Provinces Based on Satellite Night-Time Light Data. *Appl. Energy* **2018**, *231*, 1070–1078. <https://doi.org/10.1016/j.apenenergy.2018.09.200>.
61. Li, S.; Cheng, L.; Liu, X.; Mao, J.; Wu, J.; Li, M. City Type-Oriented Modeling Electric Power Consumption in China Using NPP-VIIRS Nighttime Stable Light Data. *Energy* **2019**, *189*, 116040. <https://doi.org/10.1016/j.energy.2019.116040>.
62. Liu, T.-L.; Song, Q.-J.; Lu, J.; Qi, Y. An Integrated Approach to Evaluating the Coupling Coordination Degree Between Low-Carbon Development and Air Quality in Chinese Cities. *Adv. Clim. Change Res.* **2021**, *12*, 710–722. <https://doi.org/10.1016/j.accre.2021.08.001>.
63. Wang, C.-A.; Liu, X.-Q.; Li, H.; Yang, C.-Y. Analyzing the Impact of Low-Carbon City Pilot Policy on Enterprises' Labor Demand: Evidence from China. *Energy Econ.* **2023**, *124*, 106676. <https://doi.org/10.1016/j.eneco.2023.106676>.
64. Liu, X.; Xu, H.; Zhang, M. The Effects of Urban Expansion on Carbon Emissions: Based on the Spatial Interaction and Transmission Mechanism. *J. Clean. Prod.* **2024**, *434*, 140019. <https://doi.org/10.1016/j.jclepro.2023.140019>.
65. Wu, Y.; Shi, K.; Chen, Z.; Liu, S.; Chang, Z. Developing Improved Time-Series DMSP-OLS-Like Data (1992–2019) in China by Integrating DMSP-OLS and SNPP-VIIRS. *IEEE Trans. Geosci. Remote Sens.* **2022**, *60*, 4407714. <https://doi.org/10.1109/TGRS.2021.3135333>.
66. Cengiz, D.; Dube, A.; Lindner, A. The Effect of Minimum Wages on Low-Wage Jobs. *Q. J. Econ.* **2019**, *134*, 1405–1454. <https://doi.org/10.1093/qje/qjz014>.
67. Goodman-Bacon, A. Difference-in-Differences with Variation in Treatment Timing. *J. Econom.* **2021**, *225*, 254–277. <https://doi.org/10.1016/j.jeconom.2021.03.014>.
68. Heckman, J.J.; Ichimura, H.; Todd, P. Matching As An Econometric Evaluation Estimator. *Rev. Econ. Stud.* **1998**, *65*, 261–294. <https://doi.org/10.1111/1467-937x.00044>.
69. Zhu, J.; Wu, S.; Xu, J. Synergy Between Pollution Control and Carbon Reduction: China's Evidence. *Energy Econ.* **2023**, *119*, 106541. <https://doi.org/10.1016/j.eneco.2023.106541>.
70. Yu, J.; Hu, W. The Impact of Digital Infrastructure Construction on Carbon Emission Efficiency: Considering the Role of Central Cities. *J. Clean. Prod.* **2024**, *448*, 141687. <https://doi.org/10.1016/j.jclepro.2024.141687>.
71. Song, Q.; Zhou, N.; Liu, T.; Siehr, S.A.; Qi, Y. Investigation of a “Coupling Model” of Coordination Between Low-Carbon Development and Urbanization in China. *Energy Policy* **2018**, *121*, 346–354. <https://doi.org/10.1016/j.enpol.2018.05.037>.
72. Chernozhukov, V.; Chetverikov, D.; Demirer, M. Double/Debiased Machine Learning for Treatment and Structural Parameters. *Econom. J.* **2018**, *21*, C1–C68. <https://doi.org/10.1111/ectj.12097>.

73. Zhang, C.; Miao, C.; Zhang, W.; Chen, X. Spatiotemporal Patterns of Urban Sprawl and Its Relationship with Economic Development in China during 1990–2010. *Habitat Int.* **2018**, *79*, 51–60. <https://doi.org/10.1016/j.habitatint.2018.07.003>.
74. Wang, Y.; Wang, H. Spatial Spillover Effect of Urban Sprawl on Total Factor Energy Ecological Efficiency: Evidence from 272 Cities in China. *Energy* **2023**, *273*, 127217. <https://doi.org/10.1016/j.energy.2023.127217>.

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.