International Journal of Economic Sciences

Journal homepage: www.ijes-journal.org
eISSN: 1804-9796

Spatial Spillover Effect of Heterogeneous Green Innovations on Carbon Emissions: Evidence from Yangtze River Delta Region of China

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ARTICLE INFO

Article history:
Received 3 April 2026
Received in revised form 17 June 2026
Accepted 6 August 2026
Available online 13 August 2026

Keywords:
Heterogeneous green innovation; Carbon emissions; Spatial spillover effects; Spatial econometric model; Green technology; Environmental innovation; Public R&D investment.

ABSTRACT

Green innovation is widely recognized as an effective pathway for reconciling economic development with carbon emission reduction. However, there is still no consensus on the spatial relationship between green innovation (GI) and carbon emissions (CEs). To address this gap, this study uses panel data from China's Yangtze River Delta region to examine the spatial spillover effects of GI and its subcomponents on CEs, as well as the role of public R&D investment in this relationship. The findings reveal a non-intuitive and spatially asymmetric effect of GI. Specifically, GI tends to increase CEs in the region where innovation occurs while reducing CEs in neighboring cities. Moreover, the impacts of green technologies (GTs) on CEs vary across regions and channels. Innovation in GTs, indirect CE reduction mechanisms, and direct CE reduction effects all exhibit significant regional spillover impacts on CEs. The results further show that public R&D investment, both locally and through spatial spillovers, weakens the relationship between GI and CEs. This study contributes to the literature by advancing the understanding of how different forms of green technological progress generate heterogeneous spatial spillover effects on CEs. It is among the first to systematically examine how public R&D investment moderates the relationship between GT and CEs. From a policy perspective, the findings provide practical insights into strengthening regional green innovation capacity while simultaneously reducing carbon emissions within an integrated development framework.

1. Introduction

Over the last decade, China—the world's largest carbon dioxide emitter—has positioned itself as a leading actor in the global response to climate change. The country has committed to achieving carbon neutrality by 2060 and peaking carbon emissions (CEs) by 2030, as announced to the United Nations General Assembly (UNGA) [1]. Addressing the paradox between economic growth (ER) and resource and environmental degradation under the combined pressures of economic expansion and emission reduction requires a shift toward sustainable development [2, 3]. In this context, green

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https://doi.org/10.31181/ijes1612027295

innovation (GI)[1] has been increasingly recognized as a potential solution, as it promotes energy efficiency, clean technologies, and sustainable industrial transformation [4]. However, whether GI reduces CEs remains an open and contested question, particularly when accounting for its heterogeneous forms and spatial interdependencies across regions.

Despite a rapidly growing body of literature examining the relationship between GI and CEs [5, 6], most studies conceptualize GI as a homogeneous concept, thereby overlooking its underlying heterogeneity in technological forms and managerial dimensions. Moreover, empirical evidence remains inconclusive, with studies reporting negative, positive, nonlinear, or insignificant effects [6, 7]. More importantly, the spatial spillover effects of GI, particularly how different types of green innovations affect CEs in both the implementing region and neighboring areas, remain unexplored. Furthermore, while public R&D investment is known to influence both GI and environmental outcomes [8, 9], its moderating role in the GI–CE relationship has rarely been examined from a spatial perspective. These gaps collectively motivate the present study.

To address these gaps, this study pursues two interrelated objectives. First, it systematically examines the spatial spillover effects of heterogeneous forms of green innovation on carbon emissions. Second, it investigates the moderating role of public R&D investment in shaping the relationship between different GI types and urban CEs.

From a methodological perspective, this study employs a spatial Durbin model (SDM) using panel data from 41 cities in China's Yangtze River Delta (YRD) over the period 2011–2021. In contrast to traditional regression approaches, the SDM explicitly accounts for both endogenous and exogenous spatial dependencies. This framework enables a comprehensive decomposition of effects into direct, indirect (spillover), and total impacts, thereby allowing for a nuanced assessment of how six distinct categories of GI influence CEs across space and over time.

The contributions of this study to the existing literature can be summarized as follows: (1) Most existing research implicitly assumes that GI reduces urban emissions, without fully accounting for the complex social-technical processes and diverse GIs that may shape emission outcomes differently. This study adopts a novel approach by incorporating six distinct forms of environmentally friendly innovation into an SDM, enabling the assessment of these impacts on CEs across both local and neighboring cities. (2) While prior studies have examined the relationships between GI and CE performance, or between R&D expenditure and technological innovation, few have simultaneously incorporated these factors to uncover the underlying transmission mechanisms. This study, therefore, examines how governmental spending moderates the impacts of various types of green innovation on greenhouse gas emissions. Overall, the findings provide a basis for designing more comprehensive policy frameworks that account for GI heterogeneity in regional carbon emission reduction (CER)[2] strategies.

The remainder of this paper is organized as follows. Section 2 reviews the related literature on heterogeneous green innovation and the moderating role of public R&D investment. Section 3 describes the sample, variables, spatial autocorrelation analysis, and the specification of the spatial econometric model. Section 4 presents the empirical findings, including the results of the SDM estimations, along with a series of robustness checks. Section 5 concludes the study by summarizing the main findings, along with outlining the study's limitations and future research directions.

[1] GI refers to any innovation in processes, products, services, and management which lowers damage to the environment than existing alternatives. It involves the use of innovation in technology, organization, and behavior that lowers the use of resources or production of pollutants.
[2] CER is defined as the decrease in CO_2 emissions achieved through deliberate interventions.

2. Literature Review

2.1 CEs as a result of several environmentally friendly initiatives

There is extensive research on how GI contributes to sustainable development [10], yet there is still no consensus on its relationship with CEs [11]. In general, several studies suggest that environmentally friendly innovation helps reduce CEs. For example, Többelmann and Wendler [12], in a study of 27 EU member states, found that environmental innovation, unlike general innovation, significantly reduces carbon dioxide emissions. In their study, Wang and Zhu [13] examined the impact of energy technological progress on CEs using a spatial econometric framework. They found that innovations in renewable energy technologies help reduce CO2 emissions, whereas innovations in fossil fuel technologies do not produce a significant mitigation effect. Importantly, they also found that these effects extend beyond individual regions [13].

It is also worth noting that several empirical studies report that, in certain regional or sectoral contexts, the number of green patents remains substantially lower than that of non-green patents. For example, Liu and Kang [6] found that green innovation had a more pronounced effect on reducing CO_2 emissions than non-GI, although both types of innovation significantly reduce emissions. Green technology innovation (GTI)[3] shows substantial geographical variation and indirectly reduces CEs, according to Xia *et al.,* [14], who employed a heterogeneous treatment effect model. Hao *et al.,* [15] developed a spatial econometric model using Chinese provincial data (2011-2020), suggesting that the impact of GTI on CEs varies across regions. Research on the relationship between GI and greenhouse gas emissions has produced mixed findings. Shan *et al.,* [16] reported that GTI significantly reduces CEs in the long run across N-11 countries, while its short-term effects are negligible. Using a nonlinear SDM with Chinese provincial data (2007–2019), Chen *et al.,* [3] identified an inverted-U relationship between carbon emissions and GTI, capturing both direct and interregional spillover effects. Similarly, Lu and Lu [7], combining SDM and threshold models with data from 279 Chinese cities, found that GTI exhibits spatial spillover effects and nonlinear relationships with CEs, significantly reducing intensity but having minimal impact on total emissions.

The many forms of GI have been artificially divided in some earlier research. For example, GTI has been categorized into four types: process, product, organizational, and non-innovation [10, 17]. Chen *et al.,* [18] identified two categories of eco-innovation: cleaner production and pollution prevention. Moreover, Zhao *et al.,* [19] also emphasized the distinctive characteristics of GI at the micro and macro levels. On the one hand, at the micro-level, GI encompasses activities such as green product development and manufacturing and is focused more on firm-specific developments [20]. On the other hand, GI supports ER by emphasizing the increased use of STI rather than following the development model that requires large amounts of resources, leading towards both sustainable development and better environmental quality [21]. In line with sustainable development, GT has undergone considerable changes from being solely focused on technical innovations to a wider notion involving GIs [22, 23]. The Environmental Assessment Report by the Intergovernmental Panel on Climate Change (IPCC) identifies GI in the following categories: transportation, energy efficiency, nuclear energy, waste management, and mitigation policies, regulations, and designs related to climate change. Nonetheless, few studies examined the influence of different types of GI on the performance of CEs mitigation. In their study, Xu *et al.,* [5] employed information from 218 cities at

[3] GT/GTI are technologies that have been explicitly designed for tackling environmental issues, with an emphasis on minimizing carbon emissions. This research considers GT as a subset of GI. Different from GI in general, GT focuses only on the technological and engineering aspects, whereas GI includes innovations in terms of organizations and administration as well.

the prefecture level in China, and four models were utilized for evaluation. According to them, all types of GI enhanced CE performance, except for GD innovations and innovations aimed at reducing CEs directly, whose impact was less influential. Therefore, some types of GI may be related to CEs in particular locations.

Most literature suffers from two major drawbacks. First, the idea of green innovation is generally treated as a homogeneous concept, where authors make an implicit assumption that all green innovations have the same effect on the environment. This assumption overlooks some important differences between various categories of GI. For example, while technologies aimed at improving energy efficiency and saving natural resources are likely to generate rebound effects, other green innovations, e.g., those focusing on end-of-pipe treatment of industrial wastes, could merely shift pollution from one location to another. Moreover, there is a significant lack of consideration of spatial relationships.

In this study, "GI" is considered any innovation that improves an existing Environmentally Sound Technology according to UNFCCC IPCC Green Inventory. The paper classifies GI into six categories, as mentioned in Xu *et al.,* [5], which include reduction of CEs, indirect reduction of CEs, energy-saving innovation, end-of-pipe treatment innovation, green administration innovation, and GT innovation.

2.2 Heterogeneous spatial spillovers

Another stream of research has explored the spatial spillover impacts of GI on CEs. According to Wang and Zhu [13], renewable energy innovations decrease CO_2 emissions both in the initiating region and in the nearby regions, but such effects are absent from fossil fuel innovations. Lu and Lu [7], through an analysis using data from cities in China, found that GTI creates notable spatial spillover effects despite not having any impact on overall emissions, even though it brings down emission intensity significantly. Fang *et al.,* [24], using data from the Yangtze River Economic Belt, found that GI improves urban carbon emission efficiency through spatial spillovers, which, however, depends on the absorptive capacity of the region.

Notwithstanding the above-mentioned improvements, there has been a noticeable absence of any distinction between different types of GI in current literature on GI's spatial effects. Researchers have mostly considered a single measure for all types of green patents and assumed that each type of GI will contribute equally towards the creation of spatial spillovers. This is one of the major limitations. For example, innovations aimed at reducing emissions are typically capital-intensive and specific to their locations. Consequently, such innovations may create minimal spatial spillovers. On the other hand, green administrative innovations (such as environmental management systems) can be relatively inexpensive and highly imitable. Ignoring such heterogeneity can lead to biased coefficient estimates and, consequently, misguided policy implications.

The issue of specifying the weight matrix is important in this body of literature. Most studies have used geography alone to specify the weights matrix, which results in neglecting economic linkages such as trade links, investment relations, and knowledge spillovers, which are essential conduits of innovation diffusion. In addition, many models of spatial econometrics assume symmetric spillover effects, despite recent evidence that spillover intensities differ significantly between high- and low-innovation areas. More recent studies have shown through the work of Bhowmik *et al.,* [25] and Sahoo *et al.,* [26] the importance of using techniques like multi-criteria decision-making and fuzzy systems to evaluate green policies. It is likely that standard econometric models are not adequate to explain the complex relationship between green innovation and emissions.

2.3 Moderating effect of public R&D investment

In contrast to the features exhibited by technological advances in general, GI is marked by its capital-intensive nature, lengthy gestation period, spillover effect of knowledge, and externality in terms of dependence on policy [27, 28]. Government policy instruments that are used in dealing with market failure include various measures designed to steer industry in its proper course. On the one hand, the use of government subsidies could solve the market failure considering the positive environmental externalities generated by GI. On the other hand, a traditional policy response to solve information spillover is public financing of R&D [29]. These policies work through the following two primary mechanisms: R&D additionality, where subsidies lead to the addition to the capital of companies through direct financial assistance, and behavioral additionality, where subsidies prompt companies to engage in additional innovation through changing their incentives for strategy [30]. Nevertheless, such governmental subsidies could give rise to opportunism in the form of strategic innovations, rent seeking, and even false reporting [31].

Given that financial constraints constitute a major challenge to the implementation of GI, the government can play in overcoming the lack of funding for green R&D. Empirical studies have revealed that public R&D funding positively contributes to the success of GI. In this regard, Feichtinger *et al.,* [32] observed that companies are more capable of growing sustainably due to their R&D investments. According to Fan and Teo [9], R&D spending favors GI to some extent but is detrimental above a particular level. Other researchers have focused their attention on the association between R&D and CEs. In their study, Fernández *et al.,* [33] found that R&D investments play a role in lowering CO_2 emissions in developed nations. As time passes, the impact of R&D on CEs changes. This was established by Churchill *et al.,* [34] through a panel data analysis of the G7 economies. An empirical study on the regional spillovers of GTI on CEs using panel data from 254 Chinese cities was conducted by Liu [35]. The findings showed that government funding for R&D lowers the effects of environmentally sound technological innovations on CEs. Thus, it further enhances the negative impact following the turning point in the inverted “U” shape while intensifying the positive impact before the turning point. While previous researchers have started looking at the role of government subsidies as a moderator in relation to carbon reduction via GTI, the unique characteristics of the various types of GI can result in the different impacts of these subsidies. As the six different forms of GI emphasize varied perspectives of supporting sustainable development, it is essential to research the role of public R&D spending as a moderator.

The findings of this systematic review resonate with a broader literature stream that emphasizes the constraining role of environmental uncertainty (EU) on corporate behavior. For instance, a recent systematic review by Tao *et al.,,* [36] synthesizes evidence that heightened EU, originating from geopolitical shocks, policy volatility, and market turbulence, consistently leads firms to adopt precautionary measures. Crucially, their review underscores that EU significantly raises external financing costs and can lead to a slowdown in investment. This insight is particularly relevant for our study, as government R&D investment can be viewed as a critical policy instrument that serves to mitigate EU by providing stable, long-term signals and reducing financing constraints. Therefore, examining the moderating role of public R&D expenditure within a spatial context allows us to understand how policy interventions can counterbalance the risk of EU.

2.4 Summary of gaps and the present study

In conclusion, it is clear that while there have been substantial advancements in literature regarding the GI-CE link, there are still critical areas that have remained largely unexplored. Firstly, there is little incorporation of heterogeneity in GI in spatial spillovers. Secondly, the spatial dimension of GI-CE dynamics has also been inadequately addressed due to simplifications of the specification used in the studies. Third, the moderating effect of public R&D expenditure has been mainly studied outside spatial considerations without considering various forms of GI. Fourth, although there have been many developments in the area of multi-criteria decision analysis methods [25, 26] and AI-driven risk management approaches [37], such methodological innovations have not been adopted in the study of the GI-CE relationship through spatial econometrics.

In order to address the aforementioned challenges, the current study provides a robust spatial framework by breaking down the concept of GI into six different groups. It uses an SDM that combines geographic and economic distance-based weights in its weight matrix, and looks at both the direct effects and the moderating role of public R&D expenditure on localities and spatial spillovers on the interaction between heterogeneous GI and carbon emissions in cities. In doing so, the current study helps to settle the long-standing debate about the efficacy of green innovation in lowering carbon emissions.

3. Data and Methodology

3.1 Samples and variables

Data utilized in this paper represents a balanced panel from a selection of 41 cities within the Chinese YRD to allow for examining the trends over time and evaluating how different forms of green technology impact CEs in various locations. The Chinese YRD, which consists of one municipality (Shanghai) and three provinces (Anhui, Zhejiang, and Jiangsu), is an important part of the country's ongoing process of restructuring and transforming its environment. Despite representing less than 4% of China's landmass, this region accounted for almost 25% of the country's total foreign trade earnings in 2020 and more than 33% of R&D expenditures. The decades of relentless industrialization and urban development have been responsible for the quick pace of economic development, but at the same time have increased pressure on resources and the high levels of CEs [24]. It is imperative to promote the integrated development of the YRD as part of the important strategy of the Chinese government. Eco-green integrated development is one of its greatest achievements. In order to achieve the goals of carbon peaking and carbon neutrality, it is very important to foster GI, taking into account the strengths of the YRD in terms of population, ER, science, and technology. Therefore, using the YRD as the study sample is fully representative.

Carbon dioxide emissions (*Cp*), which form the dependent variable in this study, are calculated according to the energy use pattern using a method that is recommended by the Intergovernmental Panel on Climate Change (IPCC) [5]. It should be emphasized at this point that C_p only refers to the emissions as a result of burning fossil fuels in different sectors because of the limitation in data availability. It should also be mentioned at this point that CE data are available for all cities in China.

In addition, GI is one of the primary independent variables in the research. The number of green patents (*Gp*) is used as a proxy for GI [5]. To identify *Gp*, this study employs IPC codes derived from the IPC Green Inventory maintained by the World Intellectual Property Organization, including green technology patents (*Gpt*), green design patents (*Gpa*), end-of-pipe treatment patents (*Gpep*), energy conservation patents (*Gpe*), indirect carbon emission reduction patents (*Gpi*), and direct carbon emission reduction patents (*Gpd*). Data on *Gp* for the 41 cities were obtained from the China National Intellectual Property Administration.

Further, public research and development (R&D) expenditures are included in order to test for any possible mediating role in the relationship between CEs and GI. This variable has been computed as the proportion of public spending on research and development by local government out of total public expenditures [38]. Data has been sourced from the China Statistical Yearbook on Information Technology and Science.

Drawing on the existing literature [5, 24, 39], this study selects six control variables capturing economic, social, resource, and openness dimensions: population density (*Pd*), industrial structure (*Ins*), openness level (*Fdi*), urbanization level (*Urb*), economic development level (*Gdp*), and infrastructure level (*Inf*). Population density (*Pd*) refers to the number of residents per unit area in a given region. Industrial structure (*Ins*) is proxied by the share of value added from the secondary sector in GDP. Economic development (*Gdp*) is measured by GDP per capita for each city. Urbanization level (*Urb*) is represented by the proportion of the urban population. Openness (*Fdi*) is measured by the ratio of foreign direct investment to GDP. Infrastructure level (*Inf*) is proxied by road area per capita. Data for constructing these control variables are compiled from China's Statistical Yearbook (third edition), Industrial Yearbook, and Urban Statistical Yearbook. Information from the Municipal Statistical Yearbook was used to fill in the gaps. All control variables are log-transformed to mitigate potential heteroscedasticity and multicollinearity.

3.2 Analysis of spatial autocorrelation

Spatial autocorrelation relies on statistics to evaluate how much association there is between geographic locations regarding certain events or attribute values. The general characteristics of spatial correlation can be assessed using global spatial autocorrelation. In this context, the global Moran's I index is commonly used to measure it:

$$\text{Moran's I}=\frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i-\bar{x})(x_j-\bar{x})}{S^2\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \tag{1}$$

where, $S^2=\frac{\sum_{i=1}^{n}(x_i-\bar{x})^2}{n}$ represents the sample variance, x_i is the observed value for area *I*, and *n* is the number of areas. The term w_{ij} denotes the elements of the spatial weight matrix. Regional disparity in economic status will be used to determine the spatial weight matrix in this research. In order to test the sensitivity of the model, a geography-based weight matrix was also created.

The spatial weight is defined as the inverse differences in real GDP per capita across all cities included in the study [40]. At a given significance level, a higher absolute value of Moran’s I indicates stronger spatial correlation.

The neighborhood is used to ascertain if comparable or dissimilar observed values congregate in nearby areas. The formula (2) displays the expression:

$$I_i=\frac{\sum_{i=1}^{n} W_{ij}(X_i-\bar{X})(X_j-\bar{X})}{S^2} \tag{2}$$

When $I_i > 0$, it indicates that a city's attribute values are similar to those of the neighboring regions (high–high or low–low clustering). Conversely, when $I_i < 0$, it implies dissimilarity with adjacent areas (high–low or low–high patterns).

3.3 The spatial econometrics model

The SDM model will be used to examine spillover effects from heterogeneous GI on CEs with regard to space. The SDM model is a more flexible approach relative to the Spatial Autoregressive Model (SAR) and the Spatial Error Model (SEM) since it incorporates endogenous spatial lags of the dependent variable, exogenous spatial lags of the independent variable, and a spatially lagged error term. Such flexibility becomes necessary since there might be a multitude of channels that enable GI effect transmission spatially. In addition, this approach reduces potential bias or inconsistency in parameter estimation arising from spatial dependence in the error structure, making it more generalizable [3]. The SDM can be expressed as follows:

$$y = \rho WY_{it}+X_{it}\beta+ \theta WX_{it}+\mu_i+\mu_t+\varepsilon_{it} \tag{3}$$

where Y_{it} is the dependent variable; X_{it} denotes the explanatory variables; ρ and θ represent spatial regression coefficients; and μ_i and μ_t capture spatial and temporal fixed effects, respectively. ε_{it} denotes the random error term, and W is the spatial weight matrix. Based on the selected variables and Equation (3), the specific spatial econometric model can be rewritten as Equation (4):

$$Cp_{it}=\alpha_0+\alpha_1 Gp_{it}+\alpha_2 X_{it}+\mu_i+\mu_t+\varepsilon_{it} \tag{4}$$

where $\mathrm{Cp_{it}}$ indicates city i's CEs in year t; $\mathrm{Gp_{it}}$ denotes the six different categories of Gp; α_1 represents the GI's spatial spillover coefficient; and X_{it} denotes the control variables.

To examine how public expenditure on research and development affects CEs and GI, Equation (4) is modified by adding the interaction between R&D expenditure (RD) and GI ($\mathrm{Gp_{it}}$):

$$Cp_{it}=\alpha_0+\alpha_1 Gp_{it}+\alpha_2 Gp_{it}\times RD+\alpha_3 X_{it}+\mu_i+\mu_t+\varepsilon_{it} \tag{5}$$

In the estimation process, the selection of a suitable spatial econometric model needs to be considered. Table 1 presents the outcomes from the LM test, robust LM test, Wald test, and Hausman test. Each test's null hypothesis states that the SAR and SEM models are more relevant to choose compared to SDM because the latter model could be reduced to both SAR and SEM. All findings in Table 1 are rejected by the null hypothesis at the 1% level of significance. The null hypothesis is rejected at the 1% significance level by all tests, showing that the SDM model is the best for this research. Furthermore, the results from the Hausman test also reject the null hypothesis at the 1% level of significance. Hence, a fixed-effects SDM is adopted to examine the regional spillover effects of GI on CEs.

Table 1
Results of the LM, Hausman, Wald, and robust LM tests

Statistical Tests	SLM		SEM	
	Z-value	P-value	Z-value	P-value
LM test_BM	3.430	0.064	16.685	0.000
LM test_MM	15.847	0.000	29.721	0.000
Robust LM test_BM	4.948	0.026	18.202	0.000
Robust LM test_MM	0.589	0.443	14.463	0.000
Hausman test_BM	43.83	0.000	58.10	0.000
Hausman test_MM	39.69	0.000	55.50	0.000
Wald test_BM	23.24	0.032	27.51	0.071
Wald test_MM	36.73	0.000	43.21	0.000
LR test_BM	16.08	0.0653	1103.98	0.000
LR test_MM	17.63	0.0397	1102.14	0.000

Note: BM stands for the baseline model where no moderating effect is present; MM stands for the modified model considering the moderating effect.

4. Results and Analysis

4.1 Spatiotemporal analysis

In order to show the geographical distribution of CEs and GI over time, the current study uses quartile maps to conduct a preliminary exploration of data between 2011 and 2021 with the help of

ArcGIS software. Specifically, the three representative years, i.e., 2011, 2016, and 2021, have been chosen for examination.

4.1.1 Spatiotemporal evolution of GI

The quartile map on the distribution of GI in the urban areas of the YRD is shown in Figure 1. The findings suggest that there was an overall increase in GI in YRD from 2011 to 2021. Spatially, high GI values are found in the southeastern region of YRD, while relatively low GI values are found in northern and western parts of YRD. Secondly, the city of Shanghai consistently leads other cities in YRD in GI. Also, GI growth has been very fast for Suzhou, Nanjing, Hangzhou, and Hefei, achieving much greater heights by 2021. Lastly, there is a distinct pattern of spatial clustering in cities with varying levels of GI. Most high-GI cities are clustered around Shanghai, with other clusters emerging around Suzhou and some provincial capitals.

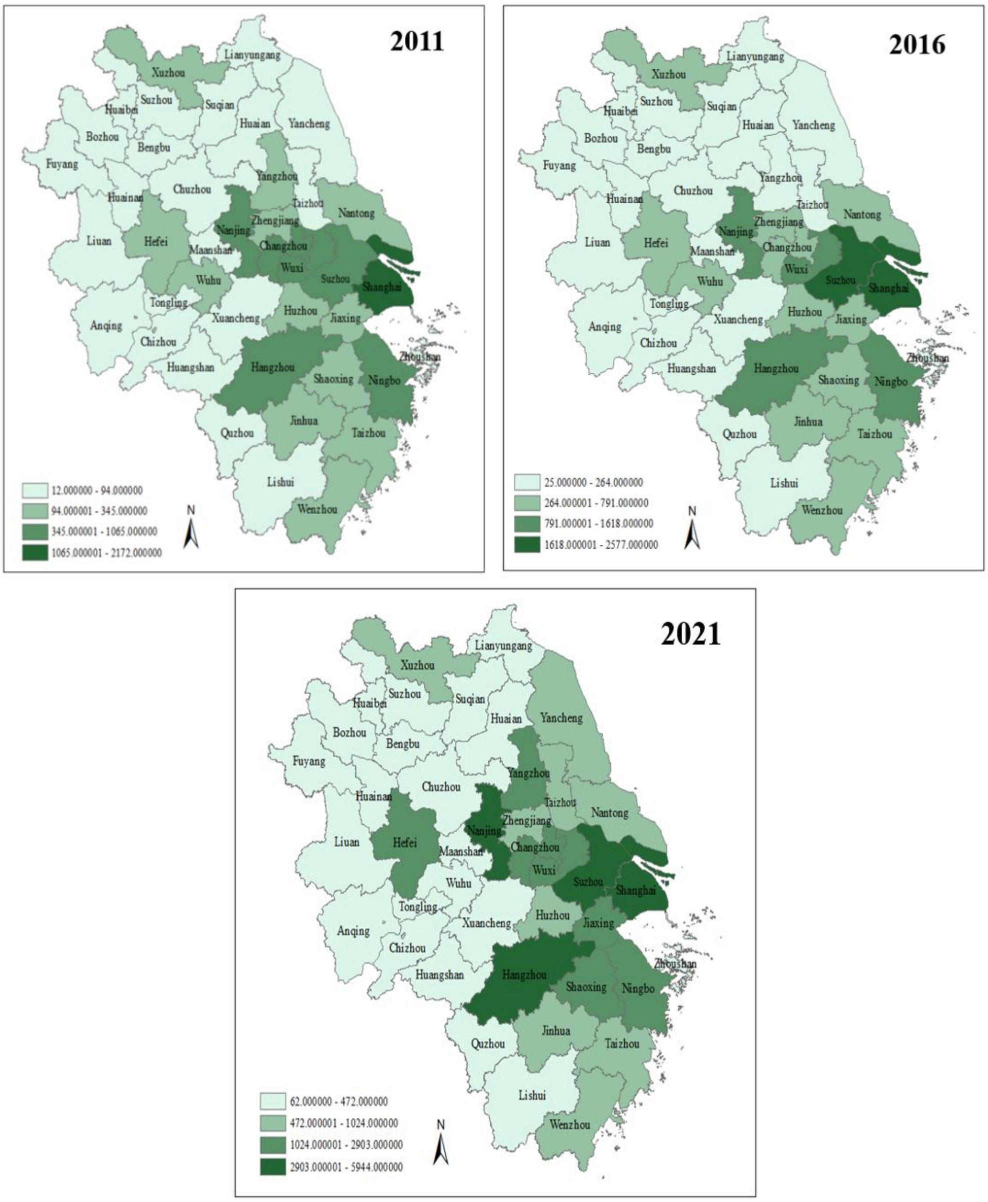

Fig. 1. Spatiotemporal distribution of GI.

4.1.2 Temporal and spatial study of CEs

Figure 2 displays the urban CE quartile maps for China's YRD area. First, Figure 2 shows that from 2011 to 2021, total CE in the YRD increased. The eastern and southeastern coastal regions exhibit higher CE levels than other regions. Second, as typical industrial agglomeration areas in China, Shanghai and Suzhou have consistently exhibited the highest CE levels in the YRD. Compared with 2011, CE in Nanjing, Xuzhou, and Ningbo, which experienced higher growth rates in industrial production value, has increased significantly. Third, overall CE levels across all cities exhibit clear spatial aggregation characteristics.

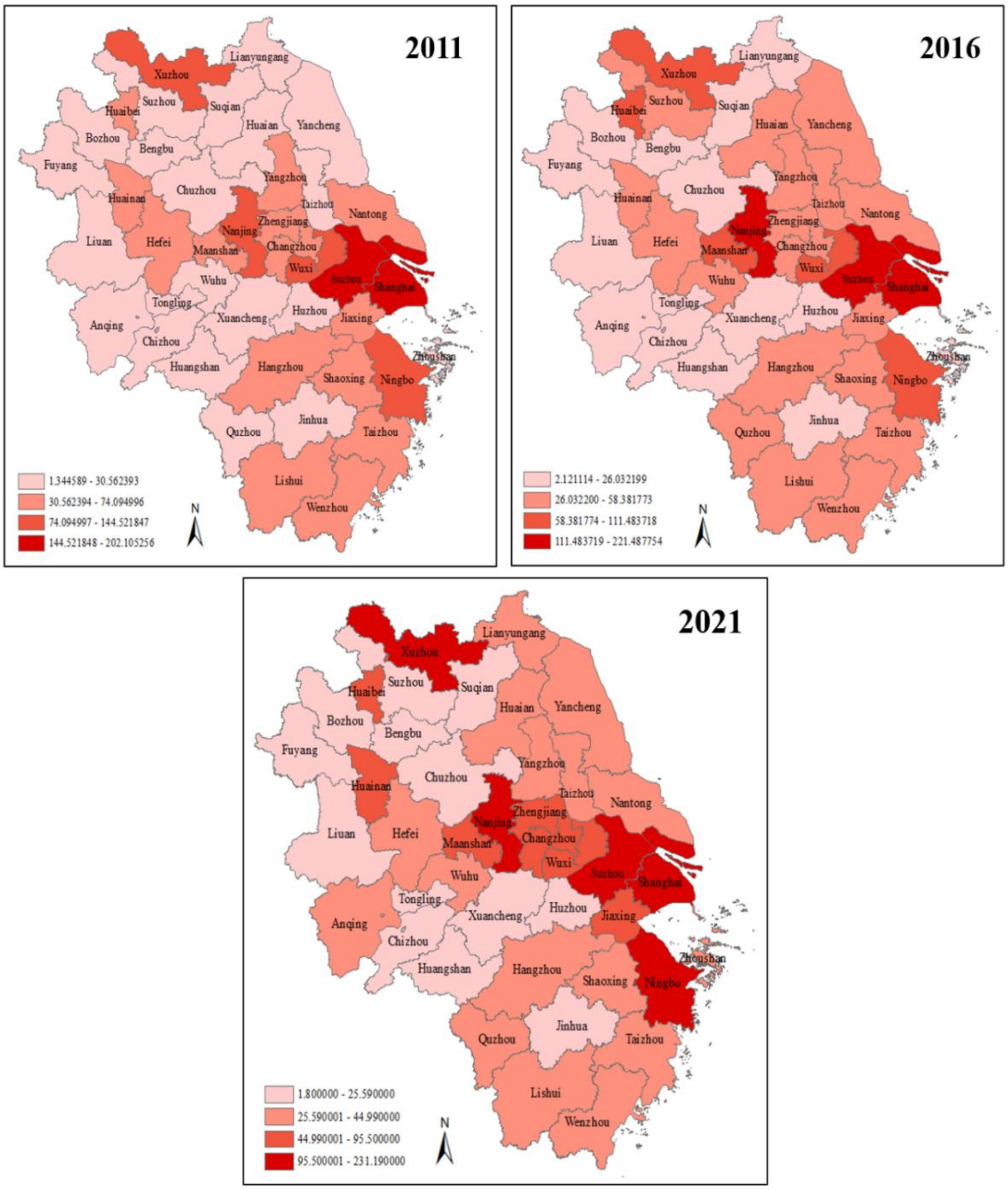

Fig. 2. Temporal and spatial distribution of CEs.

4.2 Investigation of geographical autocorrelation

4.2.1 Analysis of global spatial autocorrelation

A global estimate of Moran's I of CEs, calculated using STATA 16, is presented in Table 2. The results indicate that from 2011 to 2021, the global Moran's I for CEs remains statistically significant at the 1% level, suggesting that CEs are not randomly distributed across cities in China's YRD. Instead, CEs exhibit strong positive spatial autocorrelation, with Moran's I consistently positive at the global scale.

From 2011 onward, a noticeable downward trend in the spatial dependence of CEs can be observed (see Table 2). However, from 2015 onward, the global Moran's I begins to increase again, indicating a stronger spatial relationship among regional CEs.

Table 2
Comprehensive analysis of CEs at the global scale

Year	Economic Distance Weight Matrix			Geographic Adjacency Weight Matrix		
	Moran’s I	P value	Z value	Moran’s I	Z value	P value
	0.312***	0.000	4.322	0.321***	4.154	0.000
	0.324***	0.000	4.463	0.316***	4.087	0.000
	0.298***	0.000	4.141	0.315***	4.082	0.000
	0.301***	0.000	4.192	0.309***	4.028	0.000
	0.270***	0.000	3.792	0.293***	3.834	0.000
2011 to 2021	0.280***	0.000	3.907	0.308***	4.001	0.000
	0.283***	0.000	3.898	0.283***	3.653	0.000
	0.313***	0.000	4.284	0.308***	3.959	0.000
	0.307***	0.000	4.246	0.308***	3.984	0.000
	0.311***	0.000	4.123	0.321***	4.154	0.000
	0.315***	0.000	4.087	0.326***	3.999	0.000

4.2.2 Geographical autocorrelation in the local context

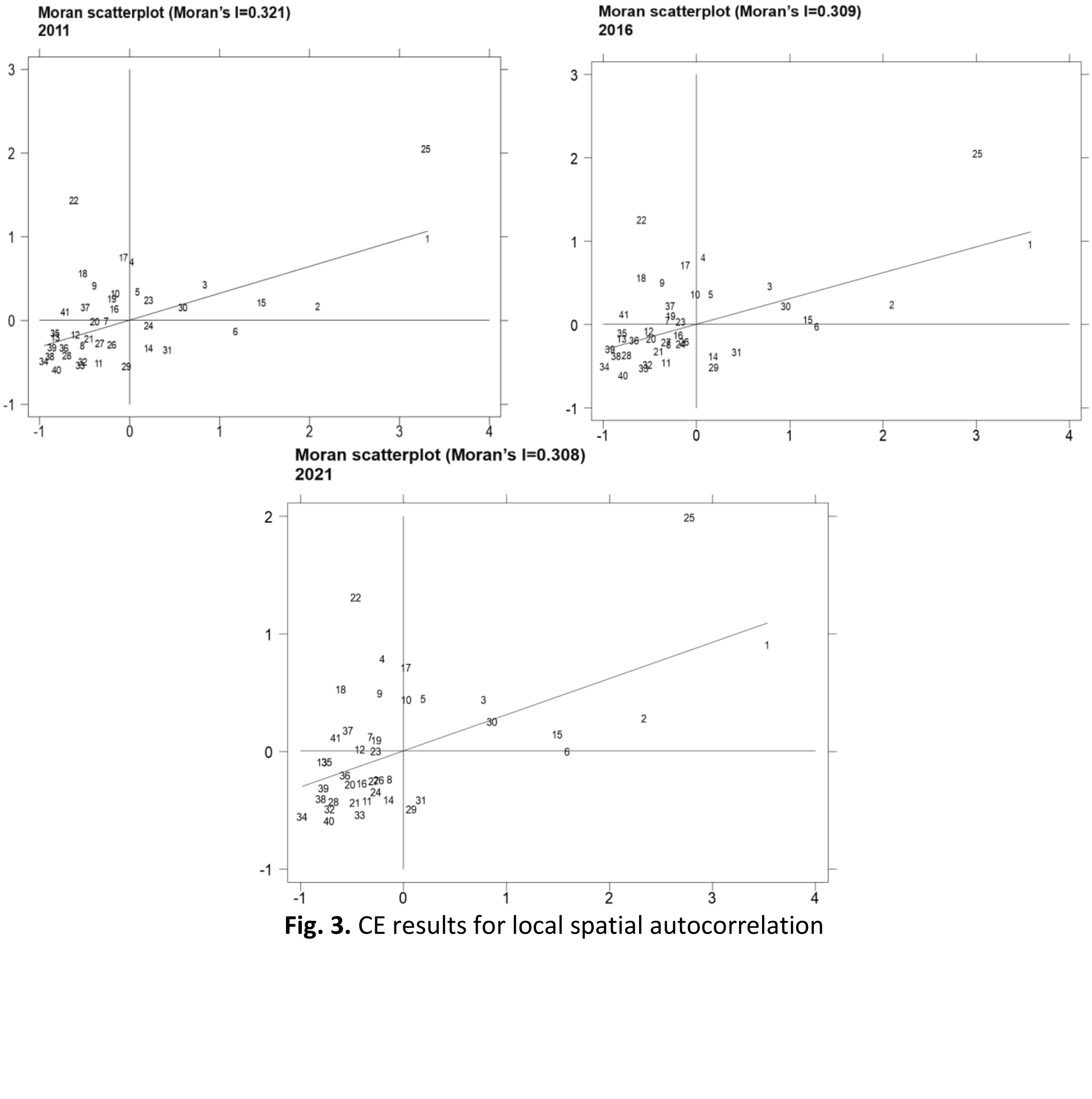

Fig. 3. CE results for local spatial autocorrelation

Note: I. Jiangsu Province, (1-13): Suzhou; Nanjing; Wuxi; Nantong; Changzhou; Xuzhou; Yangzhou; Yancheng; Taizhou; Zhenjiang; Huai'an; Lianyungang; Suqian. II. Zhejiang Province, (14-24): Hangzhou; Ningbo; Wenzhou; Jiaxing; Huzhou; Shaoxing; Jinhua; Quzhou; Zhoushan; Taizhou; Lishui. III. Municipality (Direct-Administered City), (25): Shanghai. IV. Anhui Province, (26-41): Hefei; Wuhu; Bangbu; Huainan; Ma'anshan; Huaibei; Tongling; Anqing; Huangshan; Chuzhou; Buyang; Suzhou; Lu'an; Haozhou; Chizhou; Xuancheng.

In Figure 3, the results of the local spatial autocorrelation analysis of CEs are presented.

The top two quadrants contain the majority of urban areas. Cities such as Changzhou, Shanghai, Suzhou, Nanjing, and Wuxi are located in the first quadrant and are surrounded by cities with similarly high CE levels. Suqian, Anqing, Huangshan, and Chuzhou are examples of low-low clustering cities located in the third quadrant. The number of cities in the third quadrant is higher than in 2011, providing further evidence that CEs in China's YRD region are positively and significantly spatially autocorrelated.

4.3 Examination of regression models using spatial econometrics

4.3.1 Examination of the geographically dispersed impacts of diverse GIs

Results based on SDM regression estimations are presented in Table 3.

Table 3

SDM estimation results of temporal and spatial effects

Variable	Model						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) ln Gp	0.108**						
(2) ln Gpd		0.087*					
(3) ln Gpi			0.139***				
(4) ln Gpe				-0.007			
(5) ln Gpep					0.067**		
(6) ln Gpa						0.050	
(7) ln Gpt							0.107***
ln Pd	0.790***	0.859***	0.753***	0.822***	0.770***	0.800***	0.756***
ln Fdi	0.047	0.073*	0.053	0.091**	0.088**	0.078*	0.092**
ln Gdp	-0.124	-0.053	-0.098	-0.116	-0.068	-0.084	0.043
Ins	1.487***	2.162***	1.503***	1.399***	1.346***	1.935***	1.572***
ln Inf	0.286*	0.267*	0.249*	0.281*	0.267*	0.256*	0.273*
ln Urb	2.483***	2.216***	2.353***	2.742***	2.412***	2.342***	2.185***
W×ln Gp	-1.987***						
W×ln Gpd		-1.648***					
W×ln Gpi			-2.108***				
W×ln Gpe				-1.416***			
W×ln Gpep					-0.457		
W×ln Gpa						-0.985***	
W×ln Gpt							-1.493***
W×ln Pd	-0.740	0.535	-0.973	-0.402	-0.062	-0.061	-0.702
W×ln Fdi	-0.437	-0.981***	-0.382	-0.650**	-0.734**	-0.707**	-0.788**
W×ln Gdp	1.762	1.444	1.892	1.801	0.029	0.862	1.140
W×Ins	-6.926	-3.399	-7.171**	-7.463**	-6.093	-7.217*	-8.135**
W×ln Inf	-4.439	-3.720***	-4.430***	-3.889***	-2.951***	-3.562***	-3.812***
W×ln Urb	5.422***	1.818	6.137*	4.967	3.955	3.355	6.952**
Spatial rho	-1.176***	-1.452***	-1.158***	-1.440***	-1.348***	-1.398***	-1.056***
Sigma2_e for variance	0.255***	0.240***	0.246***	0.253***	0.259***	0.254***	0.244***

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

The findings of the fixed-effects regression for total GI are presented in Column (1). Columns (2) to (7) report the regression results for different categories of GIs: GTI, GD innovation, EPTI, energy-conservation innovation, indirect CER innovation, and direct CE reduction innovation. It is noted here that there is a strong negative spatial correlation of CEs among YRD cities, consistent with the results of the spatial autocorrelation test, as indicated by the negative and statistically significant Rho values in all SDM specifications at the 1% level. The effects of different GIs on CEs vary considerably across regions, as shown in Table 3, Columns (2)-(7).

Furthermore, Table 3 reports that the estimated *ln Gp* coefficient is 0.108 and statistically significant at the 5% level. This finding adds to the growing body of evidence suggesting that green innovations contribute to increases in CEs. However, GI in neighboring cities significantly helps reduce local CEs, as indicated by the coefficient of $W \times \ln Gp$, which is -1.987 and significant at the 1% level. While certain GIs, such as those aimed at direct, indirect, or GT-related CE reduction, may increase emissions in some locations while substantially reducing them in others, this pattern is not uniform. Local CEs are not significantly affected by energy-conservation and GD innovations, whereas neighboring cities experience significant reductions in CEs due to these two factors. In contrast, end-of-pipe wastewater treatment technologies increase CEs in the directly affected area, with little or no effect on neighboring cities.

To calculate the total, indirect, and direct effects, the partial differential method is used [3]. The results are presented in Tables 4 and 5.

Table 4
Direct and indirect impacts of environmental innovations on greenhouse gas emissions

Explanatory Variables	Model (1)-(7)		
	Direct Effect	Indirect Effect	Total Effect
(1) ln Gp	0.171***	-1.048***	-0.877***
(2) ln Gpd	0.149***	-0.791***	-0.641***
(3) ln Gpi	0.206***	-1.133***	-0.927***
(4) ln Gpe	0.042	-0.630***	-0.589***
(5) ln Gpep	0.086**	-0.257*	-0.171
(6) ln Gpa	0.087**	-0.482***	-0.395***
(7) ln Gpt	0.152***	-0.841***	-0.689***

Note: ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 4 presents the decomposition of total GI effects into direct, indirect (spatial spillover), and total effects. The direct effect of GI on local CEs is positive and statistically significant (0.171), implying that a 1% increase in GI within a given city leads to a 1.048% reduction in carbon emissions in neighboring cities. The indirect effect is negative and highly significant (−1.048), indicating that a 1% increase in local GI reduces CEs in neighboring cities by 1.048%. The total effect (direct plus indirect) is negative (−0.877), indicating that, when spillover effects are considered, green innovation (GI) contributes overall to regional carbon emission reduction.

The finding that GI increases local CEs, although seemingly counterintuitive, can be explained by two interrelated mechanisms.

First, the energy rebound effect arises when green innovations improve energy efficiency, thereby reducing the marginal cost of energy services. These lower costs can stimulate increased energy consumption, partially or even fully offsetting the initial efficiency gains [41]. In rapidly industrializing regions such as the YRD, firms may respond to efficiency improvements by expanding production rather than maintaining output levels, which can ultimately lead to higher net local emissions.

Table 5
CEs as a result of control factors, both directly and indirectly

Models		Control Variable					
		ln Pd	ln Fdi	ln Gdp	Ins	ln Inf	ln Urb
(1) ln Gp	DE	0.833***	0.065	-0.184	1.759***	0.426***	2.409***
	IE	-0.808**	-0.246	0.943	-4.243***	-2.352***	1.260
	TE	0.025	-0.181	0.759	-2.484	-1.925***	3.670**
(2) ln Gpd	DE	0.879***	0.114***	-0.110	2.404***	0.409***	2.267***
	IE	-0.303	-0.488***	0.670	-2.898*	-1.819***	-0.583
	TE	0.576*	-0.374***	0.560	-0.494	-1.410***	1.684
(3) ln Gpi	DE	0.801***	0.069	-0.161	1.778***	0.386***	2.256***
	IE	-0.901**	-0.224	0.999	-4.389**	-2.340***	1.731
	TE	-0.100	-0.155	0.839	-2.611	-1.954***	3.986**
(4) ln Gpe	DE	0.871***	0.122***	-0.187	1.739***	0.428***	2.708***
	IE	-0.695*	-0.352**	0.880	-4.210***	-1.912***	0.470
	TE	0.177	-0.230*	0.693	-2.472	-1.484***	3.178**
(5) ln Gpep	DE	0.800***	0.120***	-0.077	1.621***	0.374**	2.391***
	IE	-0.493	-0.398**	0.058	-3.622**	-1.523***	0.350
	TE	0.307	-0.278*	-0.019	-2.001	-1.149**	2.741*
(6) ln Gpa	DE	0.834***	0.109**	0.122	2.286***	0.387**	2.342***
	IE	-0.518	-0.374**	0.441	-4.486***	-1.769***	0.071
	TE	0.316	-0.265*	0.319	-2.200	-1.382***	2.413
(7) ln Gpt	DE	0.791***	0.120***	0.008	1.855***	0.384***	2.064***
	IE	-0.762*	-0.465***	0.573	-5.049***	-2.123***	2.461
	TE	0.029	-0.345**	0.582	-3.195*	-1.739***	4.524**

Note: ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. DE denotes direct effect, IE indirect effect, and TE total effect.

Second, the innovation-induced scale effect occurs when GI is associated with technological progress that reduces production costs and expands economic activity. As local productivity increases, both output and energy consumption may rise, generating additional emissions that can outweigh the reductions achieved per unit of output [42]. In the present sample, the positive direct effect suggests that the scale effect currently dominates over the composition and technique effects at prevailing levels of GI.

Local GI reduces CEs in neighboring cities, a counterintuitive result that can be explained by knowledge spillovers and industrial relocation mechanisms. First, green patents generated in leading cities can diffuse to neighboring regions through inter-firm supply chains, researcher mobility, and technology licensing. This diffusion enables surrounding cities to adopt cleaner production technologies without bearing the full cost of R&D investment [13]. Second, stricter environmental regulations or stronger green innovation incentives in leading cities may induce the relocation of pollution-intensive activities to neighboring cities. However, if these relocated activities also benefit from technology spillovers and adopt greener production processes, the net effect can still be a reduction in emissions in those receiving regions. Third, the spatial weight matrix based on economic distance captures these diffusion channels more effectively than simple geographic adjacency.

Overall, the net regional effect remains negative (total effect): although the innovating city may experience short-term emission increases driven by scale and rebound effects, neighboring cities benefit from technology diffusion.

Empirical evidence on the heterogeneous emission effects across six categories of GI is presented in Table 4. Innovations in GT, green administration, end-of-pipe treatment, industrial carbon reduction (ICR), and direct CER all exhibit positive and statistically significant direct effects on emission reduction. However, green inventions as a whole tend to generate unfavorable spatial spillover effects.

This pattern suggests that direct and indirect emission-reduction technologies, such as carbon capture and air pollution control, are often codified in patents and embedded in technical standards, which makes them relatively easy to imitate and transfer across regions. As a result, these GI types generate the largest spillover coefficients in magnitude compared with other categories of green innovation.

Moreover, energy-conservation innovations exhibit no statistically significant direct effect on emissions. This result is consistent with the energy rebound effect, whereby improvements in local energy efficiency reduce energy costs and, in turn, stimulate higher energy consumption, thereby offsetting the direct reduction. In contrast, neighboring cities that adopt these technologies through spillover channels may still experience net emission reductions. This can occur particularly in regions with higher baseline energy intensity or different demand structures.

The total effect of end-of-pipe treatment innovations is statistically insignificant. End-of-pipe technologies (e.g., waste treatment and flue gas desulfurization) reduce emissions at the terminal stage without modifying production processes. Their local direct effect is positive, possibly because they enable continued or expanded production without corresponding efficiency improvements in core processes. Moreover, these technologies are often site-specific and less easily transferable, resulting in weaker spillover effects.

The findings of the control variable decomposition in Table 5 show that *Pd*, *Ins*, and *Inf* have a positive influence on total GI in local cities. This is consistent with the majority of prior research [5, 24, 43]. However, *Pd*, *Ins*, and *Inf* exhibit negative indirect effects. *Gdp* shows no significant impact on either local or neighboring CEs. Additionally, *Fdi* demonstrates significant effects on direct CE reduction innovation, energy-conservation innovation, EPTI, GD innovation, and GTI. The consistently positive and statistically significant coefficient of *Urb* warrants careful interpretation. Although urbanization can, in the long run, support green transitions through economies of scale in public transport or cleaner energy systems, the period under study (2011–2021) appears to reflect a stage in which emission-increasing effects dominate. During this time, the YRD region experienced rapid urban expansion, frequently associated with energy-intensive land use patterns and industrial agglomeration. These dynamics likely outweighed any efficiency gains that might otherwise arise from more compact urban form and improved infrastructure efficiency.

4.3.2 Moderating role of public R&D investment

To address potential multicollinearity between the core variables and their interaction terms, all continuous variables were mean-centered prior to constructing interaction terms. In addition, variance inflation factor (VIF) tests were conducted. Table 6 reports the mean-centered multicollinearity diagnostics, showing that all VIF values are below the commonly accepted threshold of 10, thereby indicating that multicollinearity is not a serious concern. Based on Equation (5), Tables 7 and 8 present the results of the spatial Durbin model (SDM) incorporating public R&D expenditure as a moderating variable, illustrating how it influences the relationship between different types of GI and urban CEs. Table 7 further indicates that, among the interaction terms, public R&D expenditure generally weakens the beneficial impact of GI on city-level CEs.

Table 6
Mean-centered multicollinearity test results

Variables	VIF	Variables	VIF	Variables	VIF
ln Gp_c	7.37	ln G×ln RD	1.49	ln Pd	5.14
Ln Gpd_c	3.06	ln Gpd×ln RD	1.63	ln Fdi	3.87
ln Gpi_c	5.25	ln Gpi×ln RD	1.51	ln Gdp	6.33
ln Gpe	6.35	ln Gpe×ln RD	1.5	Ins	1.41
ln Gpep	4.14	ln Gpep×ln RD	1.46	ln Inf	4.32
ln Gpa	4.09	ln Gpa×ln RD	1.56	ln Urb	3.96
ln Gpt	3.45	ln Gpt×ln RD	1.57		

Table 7
Results of the modified SDM incorporating the moderating variable

Variables	Model						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) ln Gp_c	0.100*						
(1) ln Gp×ln RD	1.733						
(2) ln Gpd_c		0.088**					
(2) ln Gpd×ln RD		-3.105					
(3) ln Gpi_c			0.086*				
(3) ln Gpi×ln RD			1.827**				
(4) ln Gpe_c				0.047			
(4) ln Gpe×ln RD				1.697*			
(5) ln Gpep_c					0.021*		
(5) ln Gpep×ln RD					2.800		
(6) ln Gpa_c						0.147***	
(6) ln Gpa×ln RD						-2.372	
(7) ln Gpt_c							0.006
(7) ln Gpt×ln RD							4.622***
ln Pd	0.245	0.179	0.243	0.173	0.180	0.203	0.336
ln Fdi	0.068	0.052	0.066	0.084	0.075	0.047	0.125
ln Gdp	0.107	0.163	0.124	0.103	0.158	0.102	0.310
Ins	1.838***	1.731***	1.933***	1.627***	1.507***	2.057***	1.577***
ln Inf	0.591***	0.665***	0.616***	0.650***	0.683***	0.590***	0.590**
ln Urb	0.452	0.526	0.430	0.532	0.565	0.529	0.588
(1) W×lnGp_c	-0.064*						
(1) W×ln Gp×ln RD	-2.419***						
(2) W×ln Gpd_c		-0.068***					
(2) W×ln Gpd×ln RD		-3.655					
(3) W×ln Gpi_c			-0.043***				
(3) W×ln Gpi×ln RD			-2.667				
(4) W×ln Gpe_c				-0.010*			

Table 7
Continued

Variables	Model						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(4) W×ln Gpe×ln RD				2.476			
(5) W×ln Gpep_c					-0.034**		
(5) W×ln Gpep×ln RD					-3.727*		
(6) W×ln Gpa_c						-0.115	
(6) W×ln Gpa×ln RD						2.470	
(7) W×lnGpt							-0.004
(7) W×ln Gpt×ln RD							1.596*
W×ln Pd	-0.286	-0.240	-0.289	-0.221	-0.230	-0.245	-0.309
W×ln Fdi	-0.084	-0.064	-0.082	-0.103	-0.082	-0.061	-0.070
W×ln Gdp	-0.064	-0.087	-0.067	-0.093	-0.115	-0.029	-0.198
W×lns	-1.227*	-1.051	-1.264	-0.927	-0.769	-1.278	-1.250
W×ln Inf	0.566***	0.604***	0.578***	0.610***	0.632***	0.549***	-0.667***
W×ln Urb	-0.474	-0.532	-0.440	-0.552	-0.545	-0.584	-0.8669
Spatial rho	-0.695***	-0.720***	-0.700***	-0.799***	-0.755***	-0.766***	-0.880***
R2	0.608	0.800	0.801	0.796	0.799	0.803	0.573

Note: ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 8
Direct, indirect, and total effects of the moderating variable

Variable		Direct Effect	Indirect Effect	Total Effect
(1) ln Gp	lnGp	0.028***	-1.057***	-1.030***
	ln Gp×ln RD	0.924***	-13.630***	-12.706**
(2) ln Gpd	ln Gpd	0.088***	-0.338***	-0.250**
	ln Gpd×ln RD	3.105	-9.976	-6.871
(3) ln Gpi	ln Gpi	0.086*	-0.443***	-0.356***
	ln Gpi×ln RD	1.827***	-9.829***	-8.002***
(4) ln Gpe	ln Gpe	0.047***	-0.408***	-0.361***
	ln Gpe×ln RD	1.464***	-11.428*	-9.731**
(5) ln Gpep	lnGpep	0.021***	-0.535***	-0.514***
	ln Gpep×ln RD	2.800***	-14.385***	-11.585***
(6) ln Gpa	ln Gpa	0.147**	-0.547***	-0.400**
	ln Gpa×ln RD	2.372	-3.593	1.221
(7) ln Gpt	lnGpt	0.006	-0.227	-0.233*
	ln Gpt×ln RD	4.107***	-10.876***	-6.769***

Note: ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 8 indicates that the interaction between GI and public R&D investment is associated with an increase in local CEs. One explanation is that government R&D subsidies may incentivize firms to engage in “strategic innovation”, where green technologies are patented primarily to secure financial support rather than to achieve emission reductions [31]. This can inflate patent counts, used in this study as the proxy for GI, without delivering environmental benefits. Additionally, subsidized R&D activities may tend to favor incremental rather than radical innovation, generating modest emission reductions per patent. At early stages of the green transition, public funding can also accelerate the scale-expansion effect by lowering innovation costs, which may temporarily increase local emissions before the threshold is attained.

Whereas emissions in neighboring regions decline, the indirect effect coefficients of *lnGp* and *lnGp* × *lnRD* suggest that public R&D funding substantially amplifies the adverse regional spillover effects of GI on CEs. Publicly funded green innovations are more likely to be published, shared, or licensed, thereby enhancing their accessibility to neighboring regions. Government R&D often supports basic research and pre-competitive technologies that generate positive externalities [28]. Consequently, the spatial diffusion of GI benefits is amplified when public funding promotes open science and collaborative platforms.

Some studies find that public R&D reduces CEs [33], while others report an inverted-U relationship [9]. The results attained in this study suggest that these seemingly contradictory findings can be reconciled by distinguishing between direct local effects and spatial spillover effects. At the local level, public R&D may initially increase emissions, consistent with the upward segment of an inverted-U relationship. In contrast, when spatial spillovers are accounted for, public R&D reduces net emissions at the regional level, including neighboring jurisdictions. Accordingly, studies that neglect spatial dependence or rely on spatial aggregation may reach divergent conclusions, depending on differences in geographic scope and the specification of the spatial weight matrix.

There is considerable heterogeneity in the moderating effects of public R&D expenditure across different forms of GI. For each type of GI, the interaction term exhibits a positive and statistically significant direct effect. Moreover, innovations in energy-saving technologies, GT, end-of-pipe treatment, and indirect reduction of CEs are associated with a stronger dampening effect on CEs in neighboring cities when public R&D spending increases. Public investment in R&D amplifies the moderating effects of innovations in GT, end-of-pipe treatment, ICR, and total GI (TGI) on regional CEs, based on the regression results for the overall effects. Consistent with Liu and Wang [17], public R&D expenditure moderates the relationship between GI and CEs.

4.4 Robustness analysis

The lagged endogenous variable is employed as an instrumental variable to address endogeneity concerns [44]. Specifically, lagged GI is used as an instrument to examine the relationship between GI and carbon emissions. This approach is justified on two grounds. On the one hand, lagged GI is expected to be strongly correlated with its current values, thereby satisfying the relevance condition. On the other hand, lagged GI is unlikely to be affected by current carbon emissions [45]. Accordingly, the use of lagged GI as an instrumental variable is considered appropriate for identifying the causal effect of green innovation. The regression results are presented in Tables 9 and 10. The estimated coefficients for TGI and its six subcategories remain broadly consistent with those of the original SDM, indicating that the benchmark regression results are reliable.

Table 9
Robustness test based on lagged instrumental variables

Variable	Model						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) ln Gp(IV)	0.068**						
(2) ln Gpd(IV)		0.105**					
(3) ln Gpi(IV)			0.008***				
(4) ln Gpe(IV)				-0.123*			
(5) ln Gpep(IV)					0.074**		
(6) ln Gpa(IV)						0.003	
(7) ln Gpt(IV)							0.056***

Table 9
Continued

Variable	Model (1)	(2)	(3)	(4)	(5)	(6)	(7)
W×ln Gp(IV)	-0.219**						
W×ln Gpd(IV)		-0.304*					
W×ln Gpi(IV)			-0.178***				
W×ln Gpe(IV)				-0.088			
W×ln Gpep(IV)					-0.067		
W×ln Gpa(IV)						-0.309***	
W×ln Gpt(IV)							-0.169***
Spatial rho	-0.561***	-0.480***	-0.700***	-0.478***	-0.620***	-0.389***	-0.257***
R^2	0.595***	0.618***	0.616***	0.617***	0.615***	0.620***	0.608***

Note: ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 10
Environmental innovations' direct, indirect, and total effects on greenhouse gas emissions

Explanatory Variables	Model (1)-(7) Direct Effect	Indirect Effect	Total Effect
(1) ln Gp(IV)	0.073*	-0.180***	-0.253***
(2) ln Gpd(IV)	0.105*	-0.304*	-0.199*
(3) ln Gpi(IV)	0.008*	-0.1782***	-0.186***
(4) ln Gpe(IV)	-0.123	-0.088***	-0.210**
(5) ln Gpep(IV)	0.073*	-0.214*	-0.141*
(6) ln Gpa(IV)	0.003**	-0.315***	-0.312***
(7) ln Gpt(IV)	0.056*	-0.280**	-0.224**

Note: ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Using Winsorization and an alternative spatial weight matrix, the robustness of the models is further examined. The robustness test results are reported in Table 11. First, among the key components of spatial econometric models, the spatial weight matrix plays a central role, as its specification directly influences estimation outcomes [44]. Replacing the economic distance-based spatial weight matrix with a geographical distance matrix further strengthens the model specification. In addition, Winsorization is applied to mitigate the influence of extreme values by replacing observations at the tails of the distribution with corresponding percentile values, thereby reducing the effect of outliers [46]. The results in Table 8 are consistent with those in Table 7, Column (3), confirming the robustness of the models, as both the direction and significance of the estimated coefficients remain unchanged.

Table 11
Validity test results

Variable		Model A (Replacing the spatial weight matrix)	Model B (Winsorization)
(1) ln Gp	lnGp	0.275***	0.226***
	ln Gp×ln RD	5.297***	4.524**
(2) ln Gpd	ln Gpd	0.245***	0.791***
	ln Gpd×ln RD	0.241***	0.005
(3) ln Gpi	ln Gpi	0.250***	0.410***
	ln Gpi×ln RD	0.615***	0.673***

Table 11
Continued

Variable		Model A (Replacing the spatial weight matrix)	Model B (Winsorization)
(4) ln Gpe	ln Gpe	0.080*	0.083*
	ln Gpe×ln RD	0.404***	0.001
(5) ln Gpep	lnGpep	0.653***	0.385**
	ln Gpep×ln RD	0.334***	0.199**
(6) ln Gpa	ln Gpa	0.108**	0.418***
	ln Gpa×ln RD	3.574***	4.008***
(7) ln Gpt	ln Gpt	0.024**	0.222***
	ln Gpt×ln RD	2.271***	3.132***

Note: ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

5. Conclusion

5.1 Conclusions

This study finds a growing trend and clear evidence of regional agglomeration in both GI and CEs. Counterintuitively, the regression results show that GI significantly increases CEs in the region where the innovation is implemented, while reducing emissions in nearby cities. When taken as a whole, the total effect of GI (sum of local and spillover effects) is negative and significant, indicating that GI contributes to a net reduction of CEs across the entire YRD region. Taken together, GI contributes to an overall reduction in CEs across the broader region. This finding contrasts with the traditional expectations and prior empirical studies. It is noted here that different types of green development exhibit heterogeneous spatial impacts. The empirical evidence suggests that innovations in GT, indirect innovations in CER, and direct innovations in CER all generate significant regional spillover effects. Collectively, these three forms of innovation substantially reduce CEs in certain regions. Furthermore, the analysis explores the mediating role of public research and development funding. The results indicate that government research and development spending has direct and spatial spillover effects, hence enhancing the relationship between GI and carbon dioxide emissions. In relation to all the types of GI, those of GT, end-of-pipe techniques, and ICR have the strongest moderating effects.

5.2 Implications

The spatially asymmetric effects necessitate a shift from isolated urban strategies to coordinated regional governance frameworks. High-GI cities need to negotiate with their neighboring cities for technology transfers, which can be aided by setting common targets for emissions reductions. Furthermore, a "green innovation compensation mechanism" can also be considered. For instance, cities benefiting from emission reductions in their neighbors could contribute to a regional green fund. This fund could then be redistributed to high-GI cities to offset their transitional costs and incentivize continued innovation. Whereby some of the advantages arising from regional emissions reductions are shared with high-GI cities, thereby improving overall policy efficiency.

Policymakers should move beyond aggregate GI targets and develop a nuanced policy mix that targets specific GI types. Our results indicate that innovations in green technologies, as well as direct and indirect emission reduction, generate the most significant regional spillover benefits. Therefore, public R&D funds, subsidies, and tax incentives should be preferentially channeled towards these high-spillover categories. In contrast, innovations in energy conservation and green administration, while having limited local effects, still offer positive spillovers and may be more effectively supported through diffusive policies like technology demonstration projects and management system certifications, particularly in less developed regions.

Government support, especially R&D subsidies, should not be solely based on patent counts but should be tied to demonstrable outcomes, such as achieving verified reductions in carbon emission intensity at the firm or city level, or providing evidence of technology diffusion to other local actors. This performance-based approach could mitigate strategic innovation and ensure that public funds translate into tangible environmental gains. Furthermore, in line with the findings of Tao *et al.,* [36], maintaining stable and predictable green policy frameworks is paramount. Policy uncertainty itself can negate the positive signals of R&D funding, leading firms to hoard cash rather than invest in risky, long-term green projects. Therefore, clear, long-term policy roadmaps for carbon pricing and green technology standards are essential to complement direct financial support.

5.3 Limitations and future research directions

First, this research is conducted on the Yangtze River Delta (YRD), which is highly integrated. This research cannot be generalized to regions that are either less integrated or have lower levels of innovation. There is a need for further research on other Chinese regions and cross-country contexts.

Second, this time period, running up until 2021, covers only the early and mid-phase of the carbon neutrality transition process in China. More years will be required to examine if the GI-induced effect turns negative once it surpasses some specific point, as hypothesized by the inverted U-shaped curve theory. Another approach might be to take advantage of the non-linear spatial econometric models.

Third, while this study highlights public R&D investment as the moderating variable, the micro-level mechanisms such as strategic patenting, technology transfer, and knowledge diffusion between firms have yet to be observed. An approach that uses patent records along with survey data could shed light on how the process of public investments results in spillover effects or local emissions increases. Another important aspect is that other variables should be examined as moderators, such as environmental regulation stringency and market competition, warrant further investigation.

Overcoming these limitations would enhance causal inference as well as offer more concrete guidance to formulate regionally coordinated green innovation systems.

Author Contributions

Conceptualization, Jia Wang; methodology, J.W. and H.S.; software, H.S.; validation, J.W.and H.S.; formal analysis, H.S.; investigation, H.S.; resources, H.S.; data curation, H.S.; writing—original draft preparation, H.S.; writing—review and editing, Jia Wang; visualization, Jia Wang; supervision, Jia Wang; project administration, Jia Wang; funding acquisition, Jia Wang. All authors have read and agreed to the published version of the manuscript.

Funding

This research was funded by the National Natural Science Foundation of China, grant number 42107488.

Data Availability Statement

The raw data supporting the conclusions of this article will be made available by the authors on request.

Conflicts of Interest

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

Acknowledgement
This research was funded by the National Natural Science Foundation of China, grant number 42107488.

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