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Spatial Spillover Effect of Green Industrial Agglomeration on Carbon Productivity

Jianglai Dai , Yingying Li and Xuetao Li *

School of Digital Economy, Hubei University of Automotive Technology, Shiyan 442002, China;
202410037@huat.edu.cn

* Correspondence: 20170026@huat.edu.cn (J.D.); 20060015@huat.edu.cn (X.L.)

Abstract

Green industry, as an emerging industry, plays an important role in improving regional economic and environmental performance and promoting green sustainable development. This study calculates carbon productivity using panel data from 30 Chinese provinces between 2013 and 2022. It employs the location quotient index to measure green industrial agglomeration (GIA) levels and utilizes the Spatial Durbin Model (SDM) and spatial mediation effect model to empirically examine the impact of GIA on carbon productivity (CP), its spatial effects, and the role of technological innovation therein. The results are as follows: (1) GIA not only directly enhances local CP but also exerts positive effects on surrounding regions through spatial spillover effects. (2) Spatial mediation analysis indicates that technological innovation mediates effects within regions and amplifies the positive impact of GIA on CP in surrounding areas through spatial spillover effects. (3) Heterogeneity analysis shows that regional differences in green productivity level leads to different effects of GIA on CP. Based on empirical findings, this study provides practical evidence for optimizing the spatial layout of green industries and offers policy implications for advancing China's green and low-carbon development.

Keywords: industrial agglomeration; carbon productivity; technological innovation; spatial econometrics



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1. Introduction

Scientific evidence indicates that climate change is occurring, with rising global carbon dioxide emissions driving temperature increases that lead to adverse climate consequences such as sea level rise, Arctic sea ice reduction, permafrost thawing, and high-altitude glacier melting [1,2]. This phenomenon is widely recognized as a severe threat to the sustainable development of human society [3]. Consequently, mitigating and adapting to climate change has become a paramount concern for humanity. As the world's largest carbon emitter, China faces the imperative of achieving carbon neutrality. This is crucial not only for China's overall economic and social transformation but also for the global effort to mitigate climate change [4]. Consequently, China has set targets to peak carbon emissions by 2030 and achieve carbon neutrality by 2060. However, reducing emissions does not equate to slowing economic growth. Balancing economic expansion with ecological sustainability, accelerating the low-carbon transformation of the economy, and achieving high-quality development [5] have become particularly urgent. Enhancing carbon productivity is a key pathway for China to achieve this goal. However, the development pattern driven by resources and factors, characterized by high input, high consumption, and high emissions,

has made resource constraints and environmental challenges increasingly acute [6,7]. In the context of “carbon peak and carbon neutrality”, the best way to improve carbon productivity lies in maintaining economic development on a healthy, sustainable trajectory [8]. Countries worldwide have explored two pathways to enhance carbon productivity and achieve sustainable development: First, developing green industries to shift pollution reduction from remediation to source prevention. Clean energy represents a crucial approach to reducing greenhouse gas emissions and replacing traditional fossil fuels [9,10]. The key to achieving a green energy transition lies in promoting the large-scale, clustered development of clean energy [11,12]. Second, advocating technological innovation to reduce pollution emissions at the technical level, thereby optimizing the utilization and allocation efficiency of natural resources [13,14], lowering pollution emissions across the entire product lifecycle [15], and striving to achieve maximum economic and ecological benefits at minimal environmental cost [16]. Industrial agglomeration and technological innovation are considered important mechanisms influencing carbon productivity [17]. Research indicates that stimulating enterprises’ “innovation compensation” through technological innovation is a key pathway to enhancing carbon productivity. It is recognized that industrial agglomeration influences technological progress [18,19], and technological advancement is an effective means to curb carbon emission intensity and improve carbon productivity [20]. Therefore, it is necessary to integrate industrial agglomeration with technological innovation to study their combined impact on carbon productivity. Unlike traditional industries, green industries are characterized by their environmental sustainability, knowledge-intensive nature, and innovation [21]. As energy and climate change issues become increasingly prominent, green industries have garnered widespread attention as a potential solution. A growing body of research highlights the positive impacts of green industries [22–24]. Studies have also examined the effectiveness of green industrial policies and their effects on economic and regional competitiveness [25–28]. Against this backdrop, how does the agglomeration of green industries affect carbon productivity? What are the mediating mechanisms between them? To address these questions, it is necessary to further investigate the relationship between green industrial agglomeration and carbon productivity. This should reveal the impact of green industrial agglomeration on carbon productivity, analyze the mediating role of technological innovation, as well as identifying its spatial spillover effects on surrounding areas. Answering these questions will help clarify the relationship between green industrial agglomeration and regional carbon productivity, thereby facilitating the formulation of more rational industrial support policies and more scientific innovation strategies. This will be of significant theoretical and practical value.

This paper examines the relationship among green industrial agglomeration, technological innovation, and carbon productivity. Key contributions include: First, measuring the degree of green industrial agglomeration at the interprovincial level and analyzing its spatial spillover effects on regional carbon productivity. Second, introducing technological innovation as a spatial mediating variable and employing a spatial mediation effect model to analyze its mechanism in influencing carbon productivity through green industrial agglomeration. This integration of the spatial conduction mechanism for mediating variables represents a significant methodological advancement over previous studies that solely examined localized mediating effects. In other words, this paper identifies not only the mediating role of local innovation in local carbon productivity within the transmission chain of “green industrial agglomeration-innovation-carbon productivity”, but also delineates the cross-regional mediating effects arising from the interregional flow of innovation. This reveals the pivotal role of innovation diffusion in both green industrial development and carbon emission reduction. Third, we empirically test the spatial spillover effects of green industrial agglomeration on carbon productivity using the Spatial Durbin model. Further-

more, based on the Green Productivity Index, the sample is divided into three groups: high, medium, and low, to explore the heterogeneity of the impact of green industrial agglomeration on carbon productivity. The goal of this study is to provide more robust empirical evidence for China to leverage green industrial agglomeration in enhancing carbon productivity and promoting coordinated regional green development. The rest of this paper is structured as follows. Section 2 provides an extensive overview of the extant literature, focusing on industrial agglomeration and carbon productivity, as well as green industrial agglomeration. Section 3 outlines the theoretical framework and research hypotheses. Section 4 details the construction of the econometric model and the selection of variables and data. Section 5 discusses the empirical results and robustness tests. Section 6 the conclusions and recommendations are presented.

2. Literature Review

2.1. Carbon Productivity and Industry Agglomeration

Within the low-carbon development evaluation framework, “carbon productivity” serves as a pivotal indicator linking growth and emissions reduction by incorporating “undesirable outputs” such as carbon dioxide into efficiency assessments. Scholars typically measure CP using economic output per unit of carbon emissions (GDP/CO_2) [29]. Concurrently, some scholars argue that frameworks like the DEA-SBM model and the Malmquist-Luenberger index, which assess total factor carbon productivity, can simultaneously account for multiple inputs and undesirable outputs. However, these cutting-edge methods face practical challenges in cross-regional comparisons—such as price deflators, differences in sector coverage, regional heterogeneity, and sample selection bias—leading to measurement incomparability and potential biases across studies [30]. Research indicates that China’s carbon productivity exhibits significant spatiotemporal variation [31]. It shows a fluctuating upward trend over time but displays marked spatial disparities, with eastern coastal regions far exceeding inland central and western areas [32]. These differences are profoundly influenced by factors including industrial structure, energy efficiency, technological progress, and openness levels. Among these, industrial agglomeration is considered a key spatial organizing force explaining variations in carbon productivity [33]. Industrial agglomeration is defined as the high concentration of enterprises and institutions within the same or related industries in a specific geographic area, serving as a vital spatial organizational form for regional economic development [34]. Marshallian externalities emphasize the technological diffusion and labor pool effects generated by specialized agglomeration [35–37], while Jacobsian externalities highlight the positive promotion of cross-industry innovation and integration through diversified agglomeration [38]. Early research primarily focused on the economic implications of industrial agglomeration, proposing that it significantly enhances productivity and regional competitiveness through mechanisms such as economies of scale, knowledge spillovers, and technological diffusion [39,40]. In recent years, as global environmental challenges intensify, the environmental effects of industrial agglomeration have garnered increasing scholarly attention. For instance, Zhang et al. [41] found that industrial agglomeration has a substantial impact on enhancing energy efficiency through technological spillovers. Du et al. [42] utilized Chinese enterprise data to demonstrate that both specialized and synergistic agglomerations enhance energy efficiency, though their effectiveness is influenced by the intensity of environmental regulations. Regarding industrial agglomeration and carbon productivity, theoretical and empirical research has progressively established several causal chains: scale/sharing effects [43], resource/matching effects [44], and technology/learning spillover effects [45]. On the one hand, agglomeration reduces transaction and supply chain costs by sharing intermediate inputs, thereby increasing carbon-adjusted output per unit.

On the other hand, it promotes knowledge diffusion and the spread of low-carbon/high-efficiency technologies through inter-firm proximity, ultimately enhancing energy efficiency via technological progress [46]. These positive channels embody the distinct types of externalities described by Marshall, Jacobs, and Porter, demonstrating the existence of a “green agglomeration effect”. However, agglomeration is not universally beneficial. Research also suggests that excessive agglomeration can weaken or even reverse these positive impacts due to environmental capacity constraints and resource misallocation, generating “crowding/crowding-out effects” [47] that exhibit typical nonlinear relationships. Empirical studies indicate nonlinear relationships—such as inverted U-shaped or N-shaped patterns—between industrial agglomeration and carbon productivity [33,48]. This nonlinearity is often modulated by industry characteristics, regional development stages, and policy environments.

Furthermore, the spatial spillover effects of industrial agglomeration are gaining increasing attention. Research indicates that knowledge and technology diffusion within agglomeration zones can enhance carbon productivity in neighboring areas (positive spillovers), but may also inhibit development through pollution transfer or resource competition (negative spillovers) [49]. However, existing research primarily focuses on traditional industrial agglomeration, with insufficient attention to green and low-carbon oriented industrial clusters. Moreover, there is a lack of in-depth examination of spatial spillover mechanisms and effect decomposition. This provides a theoretical entry point for this paper to examine the spatial effects of green industrial agglomeration on carbon productivity.

2.2. Green Industrial Agglomeration

As the Sustainable Development Goals advance, green industries have gradually become a focal point for academia and policymakers. Unlike traditional industries, green industries possess core characteristics of low carbon, energy efficiency, and innovation. Their essence lies in embedding environmental performance into industry practices, achieving sustainable value creation through institutional and market incentives. Green Industrial Agglomeration (GIA) refers to the spatial concentration of green industrial activities. It manifests not only as the physical clustering of enterprises but also encompasses green technology innovation networks, supply chain coordination, and supportive institutional environments [22]. Consequently, green industrial agglomeration is considered more likely than traditional agglomeration to enhance regional carbon productivity through innovation and diffusion effects [50]. Due to heterogeneity in China’s statistical methods and industry definitions, existing studies often employ alternative approaches to define green industries. For instance, renewable energy and energy-saving environmental protection equipment manufacturing are categorized as green industries [51]. Some scholars calculate annual composite pollution emission scores for each industry, classifying those below the industry median as green industries [52]. Additionally, some scholars utilize national-level ecological industrial demonstration zones as indicators of green industrial agglomeration to measure its level [53]. Regarding impact effects, research suggests that green industrial agglomeration facilitates technology and knowledge exchange, fostering the creation of more advanced “clean” technologies that reduce environmental pollution and enhance carbon productivity [54]. Moreover, as clean industries, green industries exhibit distinct geographical characteristics in their agglomeration effects. Although direct research on GIA remains nascent, relevant studies provide crucial references for this field. For instance, one study indicates that spatial agglomeration of new energy vehicle significantly drives eco-innovation [55], while another suggests an inverted U-shaped relationship between the geographic concentration of renewable energy industry and efficacy of green innovation outcomes [56]. On the other hand, more research focuses on the environmental benefits

of industrial clusters: Han et al. confirm that new energy industry clusters indirectly enhance environmental performance through green technological innovation and industrial structure upgrading, thereby promoting synergistic governance of pollution reduction and carbon emission reduction [56]. Notably, green industrial agglomeration may generate spatial spillover effects. However, extant literature is predominantly centered on the local environmental impacts of GIA, with empirical examinations of its spatial spillover mechanisms and effects requiring further exploration. Furthermore, most studies fail to distinguish between green industrial agglomeration and “brown industrial agglomeration” involving traditional industries or containing traditional sectors.

In summary, existing research provides a solid foundation for understanding the relationship among industrial agglomeration, green innovation, and carbon productivity, it nevertheless leaves key aspects unaddressed: (1) Most research focus on the economic and environmental impacts of traditional industrial agglomeration, with insufficient research on green industrial agglomeration, particularly that centered on clean energy. (2) The spatial mechanisms and effects of agglomeration on carbon productivity require further exploration. (3) The spatial mediating function of green technological innovation in this relationship and its potential nonlinear threshold characteristics remain under-explored. This study empirically tests the spatial spillover effects of green industrial agglomeration on carbon productivity and analyzes their mechanism, providing theoretical foundations and policy insights for regional green and low-carbon development.

3. Theoretical Analysis and Research Hypotheses

3.1. Direct Effect of Green Industrial Agglomeration on Carbon Productivity

The spatial clustering of economic entities facilitates knowledge dissemination, resource sharing, and the distribution of essential productive factors, thereby enhancing economic efficiency [57]. From the viewpoint of agglomeration externalities, the degree and patterns of clustering among different industries may yield distinct effects [58]. As the core driver of low-carbon economic transformation, green industries are reshaping regional sustainable development paradigms through their triple attributes: technological ecological embedding, resource recycling, and low-carbon value creation. GIA effectively reduces trade costs incurred by upstream and downstream enterprises in transportation [59], communication, and marketing, while enhancing CP by lowering aggregate energy consumption. Concurrently, expanding agglomeration scale within regions intensifies competition among homogeneous enterprises for resources and market share, fostering corporate rivalry. Heightened competitive awareness accelerates the survival of the fittest among homogeneous enterprises. Lagging firms, to avoid elimination, will either adopt or imitate the practices of leading enterprises. The released capital can elevate the overall technological level and innovation efficiency of green industries, facilitate the conversion of green low-carbon tech achievements, and boost CP. Hence, this study proposes the following research hypothesis:

H1: *Green industrial agglomeration exerts a promoting role in carbon productivity.*

3.2. Indirect Effect of Green Industrial Agglomeration on Carbon Productivity

Industrial agglomeration influences CP through multiple mechanisms. Theoretically, it impacts carbon productivity by means of scale economy, technological spillover effects, and competitive effects. Among these, technological innovation represents a key pathway for enhancing carbon productivity [60]. Studies show that heightened innovation levels can reduce carbon emissions and boost CP through improving energy efficiency, optimizing energy use, and driving local industrial upgrading [61]. Technological innovation influences

carbon productivity through both supply-side and demand-side effects. On the supply side, innovation effectively lowers production costs by enhancing labor productivity. Increased corporate capital ownership heightens firms' willingness to develop clean production technologies, carbon capture and storage technologies, and enhance energy efficiency, thereby boosting CP [62]. On the demand side, in the digital economy era, consumer awareness and demands are continuously upgrading [63]. Enterprises engage in technological innovation guided by domestic demand, offering personalized services and standardized products that effectively meet consumer needs. This gradually guides consumption patterns toward green transformation, positively impacting CP. This gradually guides consumption patterns toward green transformation, positively impacting CP. Technology exchange markets also reinforce the technological spillovers of industrial agglomeration by facilitating the flow of heterogeneous technologies, creating a virtuous cycle between technology transactions and industrial clustering. Based on knowledge spillover and technological spillover effects, spatial proximity reduces the transmission costs of tacit knowledge. As technology exchange markets expand, technological spillovers in GIA will enhance energy efficiency and CP. Accordingly, this study puts forward the following research hypotheses:

H2: *Technological innovation exerts a mediating effect on the association between GIA and CP (Figure 1), and this mediating pathway exhibits spatial spillover effects.*

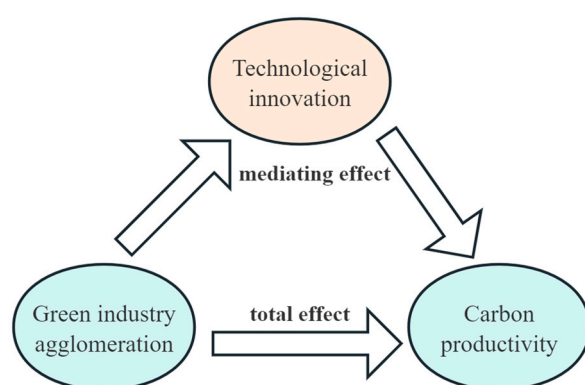


Figure 1. The mediating effect mechanism of green industrial agglomeration and carbon productivity.

3.3. Spatial Spillover Effect of Carbon Productivity

As interregional connections of production factors strengthen and economic activities expand, industrial agglomeration no longer shows spatial independence [64]. Industrial agglomeration facilitates the sharing of resources and production factors, enabling rapid dissemination of production technologies through industrial synergies within agglomerated regions. This process fosters interregional correlations in CP [65,66]. The economic linkages, information technology spillovers, and factor mobility generated by industrial agglomeration transcend administrative boundaries, influencing CP in adjacent regions [67]. Spatial correlations between CP and industrial agglomeration inevitably exist through geographic proximity and economic exchange, necessitating spatial econometric analysis to ensure the reliability of conclusions [68]. Moreover, improved infrastructure facilitates coordinated interactions between enterprises within and outside agglomeration zones, creating positive linkage effects that enhance GIA. This encourages “free-riding” green innovation behaviors among surrounding enterprises, boosting low-carbon production efficiency and reducing environmental governance costs. Additionally, a “demonstration effect” exists among neighboring firms, where competitive awareness drives mutual learning [66]. When enterprises in a region grow through agglomeration, adopt better

technologies, and produce more “green” products, surrounding enterprises learn from this model and improve CP [69]. Therefore, this paper proposes the following Hypothesis 3:

H3: *The impact of GIA on CP exhibits spatial spillover effects, and the direction aligns with that of the local area.*

4. Methodology and Data

4.1. Basic Regression Model

For the purpose of examining the relationship between GIA and CP, this study develops the following basic regression model:

$$CP_{it} = \beta_0 + \beta_1 GIA_{it} + \beta_2 X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (1)$$

In the above formula, the dependent variable CP_{it} represents carbon productivity of province i during year t , β_0 represents the constant term, GIA_{it} serves as the core explanatory variable, representing the green industrial agglomeration index of province i during year t . $\beta_2 X_{it}$ signifies the set of control variables, μ_i and λ_t represent individual and time fixed effect, ε_{it} is a random disturbance term. β_1 denotes the core coefficient, measuring the net impact of GIA on CP.

4.2. Spatial Mediation Effect Model

To evaluate the role of technological innovation, this study develops a spatial mediation effect model based on existing research findings and relevant theoretical analysis to examine the relationship between GIA and CP. The stepwise regression method put forward by Baron and Kenny [70] is a classic approach for testing mediation effects. However, considering that GIA may exert spatial spillover effects on CP in this study, and that carbon productivity itself may exhibit spatial dependency, this paper constructs a spatial mediation model to examine these effects and test the mediating role of technological innovation (TEC). This model design avoids the limitation of traditional studies that treat mediating effects and spatial effects as separate entities. The spatial mediation model is specified as follows:

$$CP_{it} = \beta_0 + \rho WCP_{it} + \beta_1 GIA_{it} + \theta_1 WGIA_{it} + \beta_c X_{it} + \theta_c WX_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (2)$$

$$TEC_{it} = \gamma_0 + \lambda WTEC_{it} + \gamma_1 GIA_{it} + \kappa_1 WGIA_{it} + \gamma_c X_{it} + \kappa_c WX_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (3)$$

$$CP_{it} = \alpha_0 + \delta WCP_{it} + \alpha_1 GIA_{it} + \varphi_1 WGIA_{it} + \alpha_2 TEC_{it} + \varphi_2 WTEC_{it} + \alpha_c X_{it} + \varphi_c WX_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (4)$$

Equation (2) examines the total spatial effect of GIA on CP (including direct effects and indirect spillover effects). Equation (3) examines the impact of GIA on the potential mediating variable TEC, while simultaneously accounting for the spatial dependence of TEC itself. Equation (4) assesses the direct spatial effect of GIA on CP and the impact of TEC on CP after introducing the mediating variable TEC, while also accounting for potential spatial spillover effects from the mediating variable itself. In Equations (2)–(4), the coefficients ρ , λ , and δ represent the spatial autoregressive coefficients for their respective equations. W denotes the spatial weight matrix. Following common practice in spatial econometrics, this study employs an Rook adjacency matrix defined as follows:

$$W_{ij} = \begin{cases} 1, & i \text{ is adjacent to } j \\ 0, & i \text{ is not adjacent to } j \end{cases} \quad (5)$$

The concrete steps for testing spatial mediation effects are as follows: First, examining whether the coefficient β_1 in Equation (2) is significant. If significant, it indicates the presence of a total effect, allowing subsequent mediation effect testing. Next, sequentially test whether the coefficients γ_1 in Equation (3) and α_2 in Equation (4) are both significant. If both are significant, it indicates a significant mediation effect. Mediation effects can be assessed by comparing the absolute values of β_1 in Equation (2) and α_1 in Equation (4). If $|\alpha_1| < |\beta_1|$, it indicates that TEC partially mediates the effect of GIA on CP.

4.3. Econometric Model

Prior to carrying out the spatial econometric analysis, it is imperative to examine whether spatial correlation is present in variables. The Global Moran's I index is a widely employed tool to assess the spatial correlation of the explanatory variables of the entire sample. This study calculates the global Moran's I index based on a spatial weight matrix constructed using the Rook adjacency rule, which undergoes row normalization. The formula for the global Moran's I index is as follows:

$$\text{Moran's } I = \frac{\left[\sum_{i=1}^n \sum_{j=1}^n W_{ij} (Y_i - \bar{Y})(Y_j - \bar{Y}) \right]}{S^2 \sum_{i=1}^n \sum_{j=1}^n W_{ij}} \quad (6)$$

Among them, $S^2 = \frac{1}{n} \sum_{i=1}^n (Y_i - \bar{Y})^2$, $\bar{Y} = \frac{1}{n} \sum_{i=1}^n Y_i$, W_{ij} represents the (i,j) -th element of the spatial weight matrix W . The Global Moran's Index ranges from -1 to 1 . A value significantly greater than 0 indicates positive spatial autocorrelation; a value significantly less than 0 indicates negative spatial autocorrelation; and a value of 0 signifies a spatial random pattern with no significant spatial autocorrelation. The global Moran's I index of carbon productivity and green industrial agglomeration in 30 provinces from 2013 to 2022 is shown in Table 1. The findings indicate that the Moran's I index exhibits statistical significance at the 10% significance level, suggesting that there exists a positive spatial autocorrelation between carbon productivity and green industrial agglomeration among provinces.

Table 1. Moran's index based on Rook adjacency.

Year	Carbon Productivity		Green Industrial Agglomeration	
	Moran's I	Z Value	Moran's I	Z Value
2013	0.3593 ***	3.1505	0.2448 ***	2.9883
2014	0.3671 ***	3.2146	0.3321 ***	3.5058
2015	0.3211 ***	2.8465	0.3623 ***	3.9460
2016	0.3455 ***	3.0337	0.5277 ***	4.9162
2017	0.3465 ***	3.0553	0.4484 ***	4.5340
2018	0.3737 ***	3.2596	0.3536 ***	3.9895
2019	0.3633 ***	3.1786	0.3886 ***	4.7406
2020	0.3414 ***	3.0105	0.4293 ***	4.5736
2021	0.2841 **	2.5493	0.3242 ***	3.6423
2022	0.1972 *	1.8572	0.3634 ***	3.7539

Notes: The values in parentheses are robust standard errors. ***, **, and * are 1%, 5%, and 10% significance levels, respectively.

To ensure the robustness of spatial autocorrelation outcomes, this study employs a geographic distance matrix as an alternative spatial weighting matrix for sensitivity analysis, with findings presented in Table 2. The Moran's I index demonstrates consistent significance across these different matrix settings, reinforcing the reliability of our findings regarding spatial dependency.

Table 2. Moran’s index based on geographic distance matrix.

Year	Carbon Productivity		Green Industrial Agglomeration	
	Moran’s I	Z Value	Moran’s I	Z Value
2013	0.0602 ***	2.8188	0.0680 ***	4.0150
2014	0.0674 ***	3.0334	0.0878 ***	4.3140
2015	0.0681 ***	3.0534	0.0909 ***	4.5869
2016	0.0701 ***	3.1068	0.1287 ***	5.2893
2017	0.0740 ***	3.2346	0.1184 ***	5.3001
2018	0.0822 ***	3.4670	0.1013 **	5.1253
2019	0.0784 ***	3.3547	0.0929 ***	5.2085
2020	0.0581 ***	2.7571	0.1055 ***	5.0833
2021	0.0413 **	2.2559	0.0818 ***	4.3405
2022	0.0158 *	1.4992	0.0880 ***	4.2666

Notes: The values in parentheses are robust standard errors. ***, **, and * are 1%, 5%, and 10% significance levels, respectively.

Lagrange multiplier tests and its robustness counterparts are employed to assess the capability of the spatial error model (SEM) and spatial lag model (SAR). If all LM test statistics pass the significance examination, additional LR and Wald tests are carried out to identify the suitability of the more general form of the spatial Durbin model (SDM). In instance where both LR and Wald test statistics demonstrate significance, the selection of SDM is made. Table 3 shows that both LM test and robust LM test values demonstrate a level of significance that exceeds the 10% threshold. Consequently, a subsequent degeneracy test of the SDM is imperative. Both LR and Wald test values are significant at the 1% level, indicating that SDM is the optimal model.

Table 3. Spatial model diagnosis results.

LM test	LM-error test	18.765 ***
	Robust LM-error test	0.029 *
	LM-lag test	21.298 ***
	Robust LM-lag test	2.562 *
LR test	LR Test (SAR)	57.72 ***
	LR Test (SEM)	57.72 ***
Wald Test	Wald Test (SAR)	62.97 ***
	Wald Test (SEM)	61.47 ***

Notes: The values in parentheses are robust standard errors. ***, and * are 1% and 10% significance levels, respectively.

4.4. Variable Definition

4.4.1. Explained Variable: Carbon Productivity (CP)

Carbon productivity combines two objectives of a low-carbon economy, including reducing carbon dioxide emissions and sustaining economic growth. Carbon dioxide emissions per unit of GDP act as the main foundation for evaluating China’s regional greenhouse gas emission control and also function as a key metric for carbon productivity assessment [71]. Based on the existing measurement approaches, the carbon productivity is measured using the ratio of GDP to total carbon emissions, the specific calculation method is as follows:

$$CP_{it} = GDP_{it}/CO_{2it} \quad (7)$$

where CP_{it} represents carbon productivity of province i in year t , GDP_{it} denotes the gross domestic product of province i in year t , CO_{2it} refers to the total amount of carbon dioxide emissions.

4.4.2. Key Explanatory Variable: Green Industrial Agglomeration (GIA)

The level of industrial agglomeration is typically measured using indicators such as the Spatial Gini Coefficient (SGC), Herfindahl-Hirschman Index (HHI), Market Concentration Ratio (SR), and Location Quotient (LQ). Among these, the Location Quotient is indicative of the level of specialization within a specific industry and has been widely applied in industrial agglomeration studies both domestically and internationally.

To clearly define “green industries” in empirical research and ensure consistency, this paper reviews two classification methods: one categorizes low-emission industries as “green” based on historical pollution or emission scores, the other uses national or local directories (e.g., ecological industrial demonstration parks, green industry catalogs). Given that energy occupies the upstream position in industrial chains and significantly impacts regional carbon efficiency, and considering the practical characteristics of China’s energy structure and the availability of provincial statistical data, this study designates hydropower, wind power, and solar power as representative green industries. The combined output value of these three clean energy sectors is used to calculate provincial green industry concentration. According to the China Energy Statistical Yearbook, these three energy sources collectively account for approximately 84% of total clean energy production. Therefore, selecting them at the provincial level effectively represents the upstream attributes of green industries while minimizing the impact of statistical heterogeneity.

The detailed formula used to calculate GIA is listed as follows:

$$GIA_{it} = LQ_{it} = \frac{gia_{it}/GIA_t}{gdp_{it}/GDP_t} \quad (8)$$

Among them, GIA_{it} represents the green industrial agglomeration in province i at year t , gia_{it} denotes the gross output value of green industries in province i during year t , GIA_t is the national gross output value of green industries in year t , gdp_{it} indicates the gross domestic product of province i in year t , GDP_t denotes the national gross domestic product in year t .

4.4.3. Mediating Variable: Technological Innovation (TEC)

To explore the possible mechanisms through which green industrial agglomeration affects carbon productivity, this study introduces technological innovation level as a mediating variable. This variable is measured by the ratio of technology market transaction volume to GDP. This indicator reflects both the commercialization level and application breadth of new technologies within a region, as well as innovation output levels, regional technology market maturity, and knowledge diffusion efficiency.

4.4.4. Control Variables

To mitigate potential confounding effects, drawing on prior research this study includes six control variables: (1) Economic development level (Agdp) is gauged by the logarithm of per capita GDP (in 10,000 yuan per person) at the provincial level. (2) Urbanization level (URB) is measured by the logarithm of the urban population size. (3) Degree of openness to the global economy (OP) is assessed using the ratio of total import and export value to GDP. (4) Environmental regulation (ER) is evaluated by the logarithm of investment in environmental pollution treatment. (5) Industrial structure (IND) is measured by the ratio of secondary industry value added to GDP. Regions with a higher proportion of

secondary industry typically exhibit greater energy consumption and carbon emissions, which may negatively impact carbon productivity. (6) Population density (PDE) is defined as the logarithm of the ratio of resident population to the area of administrative divisions. Table 4 shows a comprehensive list of the variables employed in this study.

Table 4. Variable selection and handling.

Variable	Symbol	Name	Measurement
Explained variable	CP	Carbon Productivity	$CP_{it} = GDP_{it} / CO_{2it}$
Key explanatory variable	GIA	Green Industrial Agglomeration	$GIA_{it} = \frac{gia_{it}/GIA_t}{gdp_{it}/GDP_t}$
Mediating variable	TEC	Technological innovation	The ratio of technology market transaction volume to GDP
Control variables	Agdp	Economic development level	The logarithm of per capita GDP (in 10,000 yuan per person)
	URB	Urbanization level	The logarithm of the urban population size
	OP	Openness to the global economy	The ratio of total import and export value to GDP
	ER	Environmental regulation	The logarithm of investment in environmental pollution treatment
	IND	Industrial structure	The ratio of secondary industry value added to GDP
	PDE	Population density	The logarithm of the ratio of resident population to administrative division area

4.5. Data Sources

This study covers 30 provinces (autonomous regions and municipalities directly under the central government) in China, excluding Tibet, Hong Kong, Macao, and Taiwan, with the research period spanning from 2013 to 2022. Data sources include the National Bureau of Statistics, China Statistical Yearbook, China Environmental Statistics Yearbook, China Energy Statistics Yearbook, China Science and Technology Statistics Yearbook, EPS database, CSMAR database, and provincial statistical yearbooks. Missing values are imputed using interpolation methods. Stata 18.0 statistical analysis software is employed. Descriptive statistics for all variables are presented in Table 5.

Table 5. Descriptive statistics.

Type	Variable	Observation	Mean	Std. Dev	Min	Max
Explained variable	CP	300	1.933	0.963	0.505	4.491
Explanatory variable	GIA	300	1.688	2.391	0.0176	14.29
Mediating variable	TEC	300	0.0196	0.0314	0.0002	0.191
Control variable	Agdp	300	0.754	0.188	0.344	1.279
	URB	300	3.348	0.321	2.449	3.976

Table 5. Cont.

Type	Variable	Observation	Mean	Std. Dev	Min	Max
Control variable	OP	300	0.259	0.257	0.0076	1.257
	ER	300	5.226	0.890	2.302	6.859
	IND	300	0.394	0.0771	0.160	0.558
	PDE	300	2.379	0.561	0.898	3.594

5. Analysis of Empirical Results

5.1. Results of Spatiotemporal Differentiation

5.1.1. Temporal Variations in Green Industrial Agglomeration and Carbon Productivity

Figure 2 displays the annual average values of CP and GIA across 30 Chinese provinces from 2013 to 2022, providing a preliminary overview of their temporal variation patterns. The level of GIA is represented by blue bar charts on the left vertical axis. CP is depicted by orange line charts on the right vertical axis. Overall, CP exhibits a sustained and stable upward trend, indicating that technological advancements and management optimizations related to carbon emission efficiency have achieved significant results during this period, effectively driving improvements in CP. From 2013 to 2017, the level of GIA showed a fluctuating upward trend. Since 2018, it has generally maintained a relatively high level, with minor fluctuations but consistently remaining elevated. This trend indicates that under the influence of policy support and market mechanisms, green industries have formed a certain spatial agglomeration pattern. Its evolution may be influenced by phased changes in industrial policies and regional green transition processes.



Figure 2. Overall annual average green industrial agglomeration and carbon productivity.

5.1.2. Spatiotemporal Analysis on Carbon Productivity Across China's Provinces

Figure 3 presents the distribution of interprovincial carbon productivity in China from 2013 to 2022. This heatmap visually represents carbon productivity levels through a color gradient: dark brown indicates higher values, while light green denotes lower values. Overall, eastern coastal regions such as Beijing, Shanghai, and Jiangsu exhibit higher carbon

productivity than western provinces like Xinjiang and Ningxia. Over time, most provinces transitioned from green to brown in carbon productivity, with regions like Hubei, Sichuan, and Henan showing notable improvements, reflecting the gradual effectiveness of low-carbon transformation. Some energy-dependent provinces like Shanxi and Inner Mongolia have shown steady improvement over the past decade, despite their overall lower figures. Overall, while regional variations exist in China's carbon productivity, all provinces show a steady upward trend, reflecting the nationwide advancement of green and low-carbon transformation. This provides intuitive evidence for formulating regionally differentiated emission reduction policies.

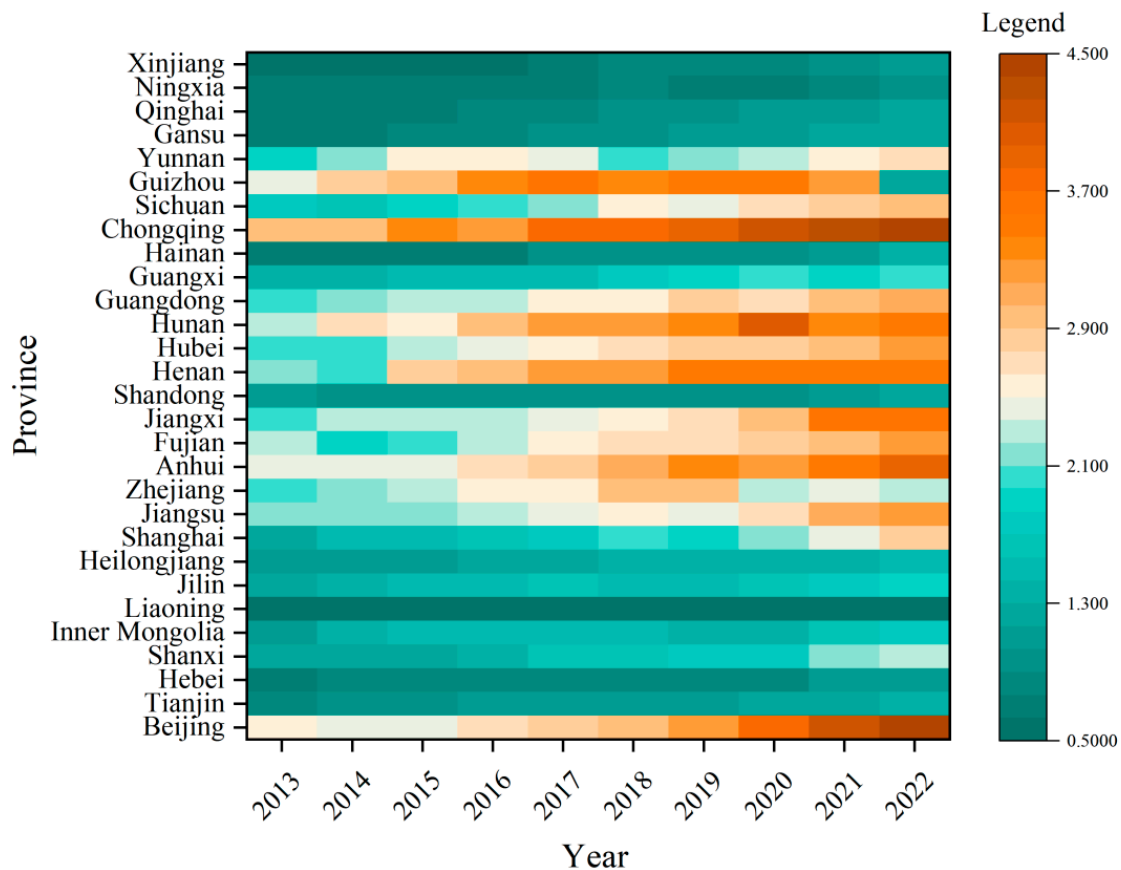


Figure 3. Carbon productivity of China's provinces from 2013 to 2022.

5.1.3. Spatial Distribution Pattern of Green Industrial Agglomeration in China

Figure 4 shows the spatial distribution characteristics of China's average GIA values from 2013 to 2022. The map employs a color gradient to represent GIA levels across four tiers, ranging from yellow (low value 3) to purple (high value 9). Overall, southeastern coastal regions such as Jiangsu, Zhejiang, and Guangdong exhibit green to yellow hues, indicating higher agglomeration levels. Central provinces like Henan and Hubei predominantly show yellow and red, reflecting moderate agglomeration. Northwestern areas including Xinjiang and Qinghai are mostly orange, signifying relatively lower agglomeration levels. Notably, one central province appears deep blue, indicating its GIA value significantly exceeds surrounding areas, forming a localized high-value center. The legend is positioned on the right, with a compass rose in the upper left corner and a 1000 km scale marked in the lower left. This distribution reveals a stepped pattern of green industry clustering in China, along with pronounced regional heterogeneity.

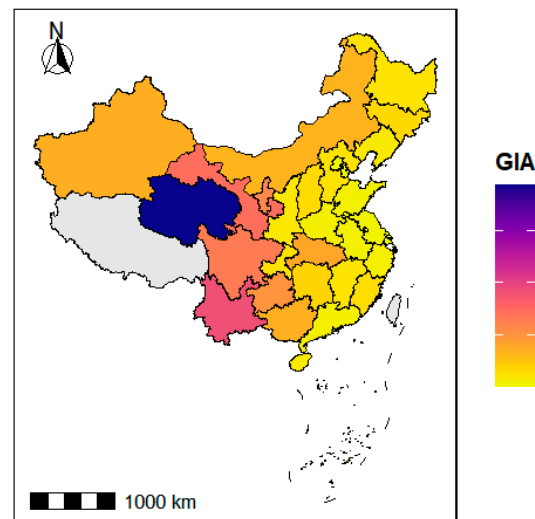


Figure 4. Spatial distribution of the average value of green industrial agglomeration.

5.2. Benchmark Regression

Equation (1) is estimated through Ordinary Least Squares (OLS) and Fixed Effects (FE) models using the entire sample. Preliminary estimates are conducted using both OLS and fixed models without considering spatial effects. Table 6 displays the regression results of the OLS and fixed models. It can be observed that the coefficients for GIA on CP are all positive, suggesting that green industrial agglomeration may enhance carbon productivity. Specifically, the OLS estimation results in Column (2) show that a one-unit increase in the GIA index significantly increases CP by 0.108 units. After incorporating individual and time fixed effects, the coefficient for GIA declined but remained positively significant at 0.040. This attenuation is both expected and reasonable, as the fixed effects model absorbs variance in the OLS model that could be explained by unobservable individual heterogeneity, thus improving the robustness and causal significance of the estimation results.

Table 6. Benchmark regression.

Variable	CP	
	OLS	FE
GIA	0.108 *** (0.026)	0.040 * (0.024)
Agdp	2.284 *** (0.331)	6.962 *** (0.982)
URB	0.808 *** (0.244)	−7.032 *** (1.511)
OP	−1.842 *** (0.291)	0.534 (0.347)
ER	0.173 ** (0.083)	0.107 ** (0.052)
IND	−1.303 ** (0.659)	−3.896 *** (0.926)
PDE	0.777 *** (0.143)	7.324 *** (2.363)
Constant	−4.442 *** (0.604)	−4.669 (4.741)
Province Fe	No	Yes
Year Fe	No	Yes
Observations	300	300
R-squared	0.3967	0.9499

Notes: The values in parentheses are robust standard errors. ***, **, and * are 1%, 5%, and 10% significance levels, respectively.

Regarding control variables, economic development level (Agdp) and population density (PDE) exhibit a significant positive correlation with carbon productivity. Conversely, industrial structure (IND), measured by the share of secondary industry, exerts an inhibitory impact on carbon productivity, highlighting the necessity of industrial transformation for enhancing carbon efficiency. The coefficient for environmental regulation (ER) is positive, validating the “Porter Hypothesis”—that appropriate environmental regulation policies can incentivize innovation and improve efficiency. Notably, the coefficients for urbanization level (URB) and global economic openness (OP) exhibit variations across different models. Urbanization generates positive externalities such as knowledge spillovers and infrastructure sharing, but also produces negative externalities including congestion, pollution, and rising land and housing prices. These negative externalities increase production and living costs, potentially inhibiting green technological innovation and resource-efficient allocation to some extent, thereby exerting pressure on carbon productivity. Against the backdrop of global industrial relocation, China may have absorbed some energy-intensive and high-emission industries from developed countries. A foreign trade structure skewed toward energy-intensive products and intermediate goods increases local carbon emission intensity, thereby reducing carbon productivity. In summary, the model with provincial and time-fixed effects performed better, with an R^2 of 0.9499, far above the OLS model, capturing most carbon productivity variations. This result provides a solid foundation for subsequent research to develop more complex spatial econometric models. These preliminary findings support Hypothesis H1.

5.3. Spatial Mediating Effects Test

To explore the potential transmission mechanisms through which GIA influences CP, this study introduces technological innovation level as a mediating variable and constructs a spatial mediation effect model. Table 7 presents the mediation effect decomposition results based on the spatial Durbin model, including direct effects, indirect effects, and total effects. It comprehensively reveals the local interactions and spatial spillover pathways among variables. Regarding GIA’s influence on the mediating variable TEC in Model (2), green industrial agglomeration exhibits not only a positive direct effect on local technological innovation but also a certain spatial spillover effect. This finding indicates that while stimulating local green technology R&D and market activities, GIA positively radiates technological innovation to surrounding regions. Furthermore, Model (3) incorporates the mediating variable TEC into the CP model to test whether and to what extent it mediates the effect of GIA on CP. This demonstrates that technological innovation is a key pathway for enhancing carbon productivity, effectively driving low-carbon transformation in both the local and neighboring areas, exerting both intra-regional and inter-regional impacts. Comparing the estimated results of GIA in Models (1) and (3) allows identification of the mediating effect. Without controlling for TEC, GIA’s direct effect on CP is 0.090 ($p < 0.01$). After controlling for TEC, this direct effect declines to 0.075 ($p < 0.01$), remaining statistically significant. Concurrently, the spatial spillover effects of GIA remain robust. Coefficient variation indicates that technological innovation exerts a partial mediating function in the GIA-to-CP influence pathway, accounting for approximately 16.7% of the mediating effect. In summary, GIA not only directly influences carbon productivity enhancement but also amplifies this effect by stimulating technological innovation activities within and surrounding the region. The regression results support the view that technological innovation mediates the impact of green industrial agglomeration on carbon productivity improvement, thereby validating Hypothesis 2. This finding provides policy implications for achieving low-carbon development through regional collaborative innovation.

Table 7. Results of mediation analysis.

Variables	Model (1) CP			Model (2) TEC			Model (3) CP		
	Direct Effect	Indirect Effect	Total Effect	Direct Effect	Indirect Effect	Total Effect	Direct Effect	Indirect Effect	Total Effect
GIA	0.090 *** (0.026)	0.138 *** (0.056)	0.228 *** (0.066)	0.002 *** (0.001)	0.001 * (0.001)	0.003 ** (0.002)	0.075 *** (0.026)	0.144 *** (0.056)	0.220 *** (0.067)
Agdp	2.857 *** (0.559)	1.328 *** (0.445)	4.186 *** (0.896)	0.079 *** (0.016)	0.015 * (0.008)	0.094 *** (0.020)	2.431 *** (0.575)	1.466 *** (0.508)	3.896 *** (0.978)
URB	0.760 *** (0.279)	0.349 ** (0.155)	1.109 *** (0.412)	−0.026 *** (0.008)	−0.005 * (0.003)	−0.031 *** (0.010)	0.923 *** (0.296)	0.559 ** (0.232)	1.482 *** (0.494)
OP	−1.994 *** (0.401)	−0.920 *** (0.293)	−2.915 *** (0.607)	−0.013 (0.011)	−0.002 (0.003)	−0.016 (0.013)	−1.899 *** (0.382)	−1.142 *** (0.354)	−3.041 *** (0.644)
ER	0.183 ** (0.094)	0.087 (0.055)	0.269 * (0.144)	0.015 *** (0.003)	0.003 * (0.002)	0.018 *** (0.003)	0.101 (0.105)	0.062 (0.069)	0.162 (0.172)
IND	−1.969 *** (0.724)	−0.923 ** (0.439)	−2.892 *** (1.107)	−0.208 *** (0.021)	−0.040 * (0.021)	−0.248 *** (0.034)	−0.793 (0.874)	−0.475 (0.550)	−1.268 (1.405)
PDE	0.650 *** (0.179)	0.296 *** (0.100)	0.946 *** (0.252)	0.012 ** (0.005)	0.002 (0.001)	0.014 *** (0.006)	0.499 *** (0.178)	0.292 ** (0.111)	0.791 *** (0.271)
TEC							6.513 *** (2.098)	4.073 ** (1.953)	10.587 *** (3.888)

Notes: The values in parentheses are robust standard errors. ***, **, and * are 1%, 5%, and 10% significance levels, respectively.

5.4. Spatial Durbin Model Analysis

In the aforementioned analysis, the spatial correlation test of the core variables has been passed. To visually clarify the impact of GIA on CP, the spatial effect was decomposed into direct, indirect, and total effects. The estimated results for the direct effect of the explanatory variable in Table 8 indicate that the impact of GIA on regional CP is positive at the 1% level, demonstrating a positive influence of GIA on CP. Regarding the indirect effect results, the spatial spillover effect generated by agglomeration is positive, reflecting that the level of industrial agglomeration within a region enhances the CP of adjacent areas. Generally, for every 1 percentage point increase in GIA levels raises provincial CP by 0.09 percentage points while boosting CP in surrounding areas by 0.138 percentage points. The spatial network effect of GIA contributes 0.228 percentage points to CP. In summary, both Hypothesis H1 and Hypothesis H3 are validated.

Table 8. Decomposition results of spatial spillover effects.

Variables	Direct Effect	Indirect Effect	Total Effect
GIA	0.090 *** (0.026)	0.138 *** (0.056)	0.228 *** (0.066)
Agdp	2.857 *** (0.559)	1.328 *** (0.445)	4.186 *** (0.896)
URB	0.760 *** (0.279)	0.349 ** (0.155)	1.109 *** (0.412)
OP	−1.994 *** (0.401)	−0.920 *** (0.293)	−2.915 *** (0.607)
ER	0.183 ** (0.094)	0.087 (0.055)	0.269 * (0.144)
IND	−1.969 *** (0.724)	−0.923 ** (0.439)	−2.892 *** (1.107)
PDE	0.650 *** (0.179)	0.296 *** (0.100)	0.946 *** (0.252)

Notes: The values in parentheses are robust standard errors. ***, **, and * are 1%, 5%, and 10% significance levels, respectively.

5.5. Robustness Analysis

5.5.1. Shortening the Sampling Period

The regression analysis above validates the core theoretical assumptions of this paper. However, considering the potential impact of factors such as estimation methods, variable selection, and time interval settings, robustness tests are necessary to ensure the reliability of the research conclusions. To this end, the model was re-estimated using data from 2016 to 2021 by shortening the sampling period. This phase comprehensively covers China's 13th Five-Year Plan period, during which the environmental policy framework matured and stabilized. This stability minimizes structural discontinuities caused by earlier large-scale radical policy shifts, facilitating the identification of market-driven GIA effects. Table 9 demonstrates that the robustness test based on 2016–2021 data effectively validates the reliability of the initial findings. It indicates that the proposed model captures not a time-specific coincidence but a stable intrinsic relationship. This confirms that the positive impact of GIA on local CP effects and spatial spillover effects constitutes a robust and reliable empirical finding.

Table 9. Result of robustness test.

Time Variables	2013–2022				2016–2021			
		CP				CP		
	Main	LR_Direct	LR_Indirect	LR_Total	Main	LR_Direct	LR_Indirect	LR_Total
GIA	0.081 *** (0.025)	0.090 *** (0.026)	0.138 *** (0.056)	0.228 *** (0.066)	0.072 ** (0.033)	0.084 ** (0.035)	0.154 ** (0.075)	0.238 *** (0.089)
Agdp	2.793 *** (0.563)	2.857 *** (0.559)	1.328 *** (0.445)	4.186 *** (0.896)	3.846 *** (0.744)	3.955 *** (0.740)	2.007 *** (0.761)	5.962 *** (1.298)
URB	0.715 *** (0.286)	0.760 *** (0.279)	0.349 ** (0.155)	1.109 *** (0.412)	0.826 ** (0.377)	0.886 ** (0.370)	0.441 * (0.230)	1.328 ** (0.563)
OP	−1.944 *** (0.402)	−1.994 *** (0.401)	−0.920 *** (0.293)	−2.915 *** (0.607)	−3.101 *** (0.611)	−3.197 *** (0.607)	−1.609 *** (0.580)	−4.806 *** (0.995)
ER	0.181 * (0.097)	0.183 ** (0.094)	0.087 (0.055)	0.269 * (0.144)	0.168 (0.124)	0.169 (0.120)	0.089 (0.077)	0.258 (0.191)
IND	−1.926 *** (0.715)	−1.969 *** (0.724)	−0.923 ** (0.439)	−2.892 *** (1.107)	−2.351 *** (0.950)	−2.414 *** (0.970)	−1.239 * (0.676)	−3.652 ** (1.550)
PDE	0.632 *** (0.168)	0.650 *** (0.179)	0.296 *** (0.100)	0.946 *** (0.252)	0.727 *** (0.227)	0.753 *** (0.242)	0.370 ** (0.154)	1.123 *** (0.355)
N		300				180		

Notes: The values in parentheses are robust standard errors. ***, **, and * are 1%, 5%, and 10% significance levels, respectively.

5.5.2. Replace the Spatial Weight Matrix

To further validate the robustness of the empirical results, this study replaces the Rook adjacency spatial weight matrix in the Spatial Durbin Model (SDM) with a geographic distance matrix. The spatial effect decomposition results using the alternative weighting scheme are presented in Table 10. The regression results under both spatial weight matrices show that GIA's direct, indirect, and total effects remain positive at the 1% level. Although the specific coefficient values exhibit slight variations due to differing weight definitions, the conclusion regarding its positive promotional effect is consistent. Furthermore, the significance levels and coefficient signs of other control variables also exhibit consistency across the two estimations. Notably, the direction and significance of both direct and total effects remained fundamentally unchanged. Some discrepancies in indirect effects likely stem from different weighting matrices capturing distinct types of spatial dependencies: the geographic distance matrix stresses absolute location, while the adjacency matrix highlights correlations from shared boundaries. Nevertheless, the core conclusions remain unchanged.

In summary, by estimating through the replacement of the spatial weight matrix, the direction and significance level of the effects for the model's core variables and key control variables remained largely unchanged. This demonstrates that the regression results of this study are robust and reliable.

Table 10. Spatial effect decomposition based on geographic distance matrix.

Variables	Direct Effect	Indirect Effect	Total Effect
GIA	0.094 *** (0.027)	1.116 *** (0.343)	1.209 *** (0.352)
Agdp	3.548 *** (0.545)	1.439 (1.365)	4.987 *** (1.563)
URB	0.894 *** (0.271)	0.348 (0.341)	1.242 *** (0.481)
OP	−2.434 *** (0.376)	−0.976 (0.920)	−3.411 *** (1.032)
ER	0.176 ** (0.090)	0.076 (0.104)	0.252 * (0.168)
IND	−1.766 *** (0.712)	−0.759 (0.843)	−2.525 * (1.329)
PDE	0.961 *** (0.150)	0.379 (0.358)	1.340 *** (0.389)

Notes: The values in parentheses are robust standard errors. ***, **, and * are 1%, 5%, and 10% significance levels, respectively.

5.6. Endogeneity Test

Considering the potential bidirectional causality between GIA and the dependent variable CP—where regions with higher carbon productivity may attract more green enterprises, thereby enhancing green industrial agglomeration—it is necessary to address potential endogeneity issues. This study employs the first-order lag term of GIA (IV1) and terrain undulation (IV2) as instrumental variables. Overall, the current development of green industries is closely linked to earlier patterns of industrial agglomeration. The impact of lagged GIA on current output levels can only be realized indirectly through contemporary GIA. Thus, the first-order lag term in the GIA model satisfies the instrumental variable requirements. Terrain undulation reflects regional topographical complexity, which historically influenced the spatial distribution of economic activities and infrastructure development—factors potentially linked to contemporary industrial agglomeration patterns. However, it is reasonable to assume that historical terrain characteristics do not directly affect current carbon productivity dynamics, thereby satisfying the instrument variable's relevance and exogeneity constraints.

Columns (2) to (5) of Table 11 presents the results of endogeneity tests conducted using two-stage least squares (2SLS) with two different instrumental variables: the first-order lag term of GIA (IV1) and terrain fluctuations (IV2). The first-stage regression results for both instrumental variables indicate a robust and statistically significant correlations between the instrumental variables and the endogenous regression variables. Their highly significant coefficients, along with the rejection of the null hypothesis for insufficient identification by the Kleibergen-Paap rk LM statistic, confirm the validity of the selected instrumental variables. Furthermore, the Kleibergen-Paap rk Wald F-statistics exceed the critical values of the Stock-Yogo weak identification test, indicating that both instrumental variables qualify as strong instruments. The GIA coefficients obtained from the two instrumental variable methods exhibit consistency in direction, magnitude, and significance. This provides evidence that the findings are not driven by endogeneity bias.

Table 11. Results of endogeneity test.

Variables	IV1: First-Stage GIA	IV1: Second-Stage CP	IV2: First-Stage GIA	IV2: Second-Stage CP
IV1 (L.GIA)	0.859 *** (0.040)			
IV2 (Terrain Und)			1.612 *** (0.119)	
GIA		0.169 *** (0.020)		0.177 *** (0.023)
Constant	0.94 * (0.497)	−5.193 *** (0.462)	3.759 *** (1.013)	−5.253 *** (0.412)
Kleibergen-Paap rk LM statistic	48.33 ***	48.329 ***	63.47 ***	63.466 ***
Kleibergen-Paap rk Wald F statistic	472.15	472.154	184.89	184.894
Control variables	Yes	Yes	Yes	Yes
Obs	270	270	300	300

Note: Standard errors in parentheses, *, and *** indicates statistical significance at 10% and 1% levels, respectively.

5.7. Regional Heterogeneity Analysis

To thoroughly examine the heterogeneity of GIA's impact on CP, this study did not adopt traditional sample segmentation methods based on geographic or administrative location. Instead, it classified the 30 sample provinces into three groups—high, medium, and low green productivity levels (10 provinces per group)—based on the Green Productivity Evaluation Index for China's Provincial Administrative Regions, conducting a heterogeneity regression analysis. This classification approach is grounded in a critical insight: the environmental effects of industrial agglomeration exhibit pronounced nonlinear characteristics and context-dependence, moderated by factors such as regional development stages, policy environments, and resource endowments [47–49]. We consider that examining the intrinsic quality dimension of green development, rather than relying solely on geographic characteristics, better reveals the underlying mechanisms and economic implications of GIA's impact on CP. This approach avoids potential confounding effects from geographic classification and more accurately identifies the differentiated mechanisms of GIA across different stages of development.

The heterogeneity analysis results (Table 12) reveal that the impact of GIA on CP exhibits group-specific differences, which aligns closely with theoretical expectations in the literature regarding the “threshold characteristics” and “development stage dependency” of industrial agglomeration environmental effects [57,58]. Within the medium green productivity group, GIA exerted the most pronounced positive effect on CP (coefficient: 0.382, significant at the 1% level). This suggests that in these regions, green industrial agglomeration can effectively drive carbon productivity growth, likely due to synergistic effects between their robust industrial foundations and favorable policy environments [42]. In the low green productivity group, GIA still exhibits a positive impact (coefficient of 0.049, significant at the 5% level), but the magnitude of the effect is substantially lower than in the medium group. This may stem from the weak foundations in infrastructure, innovation absorption capacity, and institutional environments in these regions, which constrain the full realization of knowledge spillover effects [44,45]. However, in the high green productivity group, GIA negatively affected CP (coefficient of −0.255, significant at the 1% level), consistent with other studies on the nonlinear link between industrial agglomeration and energy efficiency [41]. This result suggests that in regions with more mature green transitions, industrial agglomeration may exhibit “crowding effects” or “structural lock-in”. Specifically, excessive agglomeration could intensify resource competition, saturate envi-

ronmental capacity, and foster innovation inertia, thereby inhibiting further improvements in carbon productivity.

Table 12. Results of heterogeneity analysis.

Variable	CP		
	High Green Productivity	Medium Green Productivity	Low Green Productivity
GIA	−0.255 *** (0.070)	0.382 *** (0.099)	0.049 ** (0.022)
Agdp	2.114 *** (0.494)	5.348 *** (0.987)	1.476 *** (0.406)
URB	−0.266 (0.358)	−2.251 ** (0.955)	0.883 *** (0.264)
OP	−0.094 (0.310)	−7.593 *** (1.336)	−4.118 *** (0.593)
ER	−0.273 ** (0.139)	0.290 (0.226)	0.125 (0.091)
IND	−2.800 *** (0.139)	7.710 *** (1.971)	−1.732 ** (0.840)
PDE	−1.961 *** (0.341)	2.521 *** (0.483)	0.472 *** (0.183)
_cons	9.883 ** (1.730)	−3.840 *** (1.306)	−2.969 *** (0.734)
R ²	0.4708	0.4402	0.5093
N	100	100	100

Notes: The values in parentheses are robust standard errors. ***, ** are 1% and 5%, significance levels, respectively.

Furthermore, the differentiated performance of control variables across groups further supports the existence of regional heterogeneity. Economic development level (Agdp) positively correlates with CP across all groups, but its effect is strongest in the medium group. Industrial structure (IND) shows a negative effect in the high group but a positive effect in the medium group, reflecting the complex impact of industrial structure transformation on carbon productivity at different development stages. These findings further confirm that the carbon productivity effect of green industrial agglomeration is not a simple linear relationship but is modulated by multiple factors including regional green foundations, policy environments, and development stages.

In summary, the heterogeneity analysis reveals that the impact of green industrial agglomeration on carbon productivity is not linearly monotonic but modulated by multiple factors. This finding deepens our understanding of the boundary conditions for the “green agglomeration effect” and provides crucial empirical support for formulating differentiated regional green development policies.

6. Conclusions and Implications

6.1. Conclusions

This study utilizes panel data covering 30 provinces in China spanning 2013–2022, employing the location entropy method to measure green industrial agglomeration levels. It constructs a Spatial Durbin Model (SDM) and a spatial mediation effect model to empirically examine the impact of green industrial agglomeration (GIA) on carbon productivity (CP), its underlying mechanisms, and spatial spillover effects. Furthermore, it conducts heterogeneity analysis from the perspective of differences in green productivity levels. Key findings are as follows: (1) Green industrial agglomeration exerts a direct promotional effect and positive spatial spillover effect on carbon productivity. A one-unit increase in

local green industrial agglomeration boosts provincial carbon productivity by approximately 0.09 units and, through spatial spillover, elevates carbon productivity in neighboring provinces by about 0.138 units, yielding a total effect of 0.23 units. This conclusion remains valid after a series of robustness tests, including addressing endogeneity issues via instrumental variables, replacing the spatial weight matrix, and shortening the sample period. (2) Technological innovation plays a partial mediating role in the effect of GIA on CP, and this pathway also shows spatial spillover. GIA not only directly stimulates local technological innovation but also strengthens neighboring technology markets through spillovers, boosting carbon productivity growth both locally and in surrounding areas. This mediating effect accounts for approximately 16.7% of the total impact. (3) The influence of green industrial agglomeration on carbon productivity exhibits regional variation depending on local green productivity levels. Regression results grouped by green productivity levels show that GIA has the strongest positive effect on CP in the medium green productivity group and a similar effect in the low green productivity group. In contrast, it reduces CP in the high green productivity group, suggesting that mature regions may face “crowding effects” or “structural lock-in”.

6.2. Policy Recommendations

Drawing on the research findings mentioned above, this paper puts forward the following policy recommendations:

- (1) Improve market mechanisms and regional coordination policies. Spatial econometric findings of this study show that green industrial agglomeration not only enhances carbon productivity within the region, but also generates positive spatial spillover effects on neighboring areas. Therefore, it is recommended to further dismantle barriers to factor mobility, facilitating the market-driven flow of capital, talent, technology, and other production factors toward regions and industries with higher green efficiency to enhance factor allocation efficiency. At the same time, establishing regional coordination mechanisms can align green industrial development plans, support shared infrastructure, and promote joint environmental governance. This will better leverage the role of green industrial agglomeration in enhancing carbon productivity locally and in surrounding areas.
- (2) Strengthen spatial coordination and diffusion mechanisms for technological innovation. Spatial intermediary effect tests reveal that green industrial clusters not only can boost local technological innovation levels but also stimulate innovation in neighboring regions through spatial spillover channels. Based on these findings, policy design should emphasize the spatial coordination and externalities of technological innovation. Support should be provided for establishing cross-regional green technology cooperation platforms, encouraging the rational flow and sharing of innovation factors across regions, and guiding the formation of interregional innovation collaboration networks. This will amplify the technological spillover benefits generated by green industrial clusters, thereby better leveraging their multi-level driving role in enhancing carbon productivity.
- (3) Implement differentiated green industrial agglomeration strategies. The study findings suggest that the effect of green industrial agglomeration on carbon productivity differs among regions with different levels of green productivity. Policy formulation must fully account for this heterogeneity. For regions with moderate green productivity levels, prioritizing support and optimizing the layout of green industrial clusters can effectively enhance carbon productivity. For regions with high green productivity levels, focus should be placed on addressing potential crowding effects from clustering, striving to improve the quality of clustering and innovation efficiency. For regions

with high green productivity levels, focus should be placed on addressing potential crowding effects from clustering, striving to improve the quality of clustering and innovation efficiency.

6.3. Research Limitations and Future Prospects

Although this study offers insights and evidence for China's green and low-carbon development, it inevitably has limitations. First, constrained by data availability, this paper employs inter-provincial panel data, with green industry measurement primarily focusing on representative sectors such as hydropower, wind power, and solar power generation. Future research could integrate micro-level firm data, natural experiments, and broader definitions of green industries to better identify causal pathways. Second, carbon productivity is calculated as GDP divided by CO₂ emissions without accounting for price index deflation or regional purchasing power differences, potentially affecting comparability. Future work will explore more robust measurement using a total factor carbon productivity framework. Finally, in exploring the transmission mechanisms of green industrial agglomeration on carbon productivity, this study primarily focuses on technological innovation. Other potential pathways, such as industrial structure upgrading, energy efficiency improvements, and interactions with environmental regulations, have not been fully examined. Subsequent research could develop a more systematic mechanism analysis framework to deepen the study of these pathways.

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Abbreviations

The following abbreviations are used in this manuscript:

CP	Carbon Productivity
GIA	Green Industrial Agglomeration

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