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The Impact of Green Industrial Park Policies on Carbon Emissions under the Dual-Carbon Goals: Evidence from Prefecture-Level Cities in China

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Abstract. Traditional industrial parks (IPs) are characterized by high energy consumption, significant greenhouse gas emissions, and severe pollution, posing substantial pressure on achieving the dual goals of 'carbon peak and carbon neutrality' and the dual strategy of 'Beautiful China.' Therefore, it is imperative to explore the impact of the green low-carbon transformation of industrial parks, specifically the effects on the 'quantity' and 'quality' of carbon emissions in green industrial parks (GIPs). This study constructs a difference-in-differences (DID) model and a spatial difference-in-differences (SDID) model to analyze the impact of green industrial park policies on carbon emissions and carbon productivity in 277 prefecture-level cities from 2010 to 2021. The results indicate that the green industrial park policies significantly reduce urban carbon emissions while improving carbon productivity. To address endogeneity concerns, the study employs the data on the opening of Railways during the Republic of China era as an instrumental variable, ensuring the robustness of the results. Moreover, the study examines the heterogeneous effects of the policy and its mechanisms, finding significant differences in policy responses between resource-based cities and eastern cities. The policy achieves emission reduction and enhances carbon productivity through mechanisms such as improving energy efficiency, promoting innovation, and facilitating industrial agglomeration, and exhibits positive spatial spillover effects. The research provides empirical support and policy recommendations for China to achieve its 'dual carbon' goals.

Keywords: Green industrial park, carbon emission reduction, endogenous issues, difference-in-differences model, spatial spillover effects.

1. Introduction

The challenge of climate change caused by greenhouse gas (GHG) emissions has become a common issue faced by countries around the world (IPCC, 2018). In response to this challenge, China has proposed the goals of peaking carbon emissions by 2030 and achieving carbon neutrality by 2060 (Ministry of Commerce, 2020), and has set 2035 as a milestone for the construction of a "Beautiful China" (State Council of China, 2020). Industrial parks (IPs), as key carriers of industrial production in China, had expanded to 2,543 by 2019 (Hong and Gasparatos, 2020)[17]. Currently, more than 80% of China's industrial enterprises are concentrated in industrial parks, which contribute over 50% of the country's industrial output and about 31% of CO2 emissions (Lyu et al., 2022). Industrialization has not only driven rapid economic development but has also become an important area for air pollution control and is crucial for achieving the "dual carbon" goals of peak carbon and carbon neutrality as well as for precise emission reductions (Tian et al., 2022). Traditional industrial parks, in promoting economic growth, rely heavily on conventional energy and emit large amounts of greenhouse gases and air pollutants (Zhang et al., 2020)[42]. Therefore, guided by green development, the low-carbon and emission-reduction transformation of traditional industrial parks is essential, and the construction of green industrial parks (GIPs) has become an important tool in sustainable development strategies.

In 2016, China's Ministry of Industry and Information Technology (MIIT) issued the "Industrial Green Development Plan," proposing the promotion of green industrial park construction (MIIT, 2016), and also released the "Notice from the General Office of the Ministry of Industry and Information Technology on the Construction of a Green Manufacturing System," further emphasizing the necessity of building green industrial parks. In 2021, the State Council of China, in the "Action Plan for Carbon Peak Before 2030," stated that efforts should be made to optimize industrial layout and implement carbon reduction projects to accelerate the construction of green industrial parks (State Council of China, 2021). Green and low-carbon research has become an important part of transforming traditional industrial parks into green industrial parks. Therefore, studying the emission reduction potential of green industrial parks is of significant practical importance, as it helps alleviate environmental pressure and provides empirical support for achieving the "dual carbon" goals.

This paper uses the pilot policies of green industrial parks as a starting point, and through rigorous empirical analysis using a difference-in-differences (DiD) model, systematically examines the impact of green industrial park policies on the 'quantitative reduction and qualitative improvement' of carbon emissions. The study provides a comprehensive analysis of the emission reduction effects of green industrial parks from the perspectives of policy effectiveness, heterogeneity, and spatial spillover effects, offering scientific evidence and practical guidance for regions to formulate innovative emission reduction policies based on their economic development stage and achieve the 'dual-carbon' goals.

The structure of this paper is as follows: Section 2 provides a literature review; Section 3 presents an analysis of the theoretical mechanisms; Section 4 introduces the model setup and data description; Section 5 discusses the empirical results; Section 6 offers an in-depth analysis of the spatial spillover effects of the green industrial park policy on the 'quantity reduction and quality improvement' of carbon emission reductions, including heterogeneity and mechanism analysis; and Section 7 concludes the paper.

2. Literature Review

The Green Industrial Park Policy is a platform that emphasizes green concepts and requirements for the agglomeration of production enterprises and infrastructure, focusing on the overall management and collaborative linkage among factories within the park. Promoting the greening of the park requires implementing resource conservation and environmentally friendly concepts in multiple aspects such as planning, spatial layout, industrial chain design, energy and resource utilization, infrastructure, ecological environment, and operational management, in order to achieve a green park characterized by layout agglomeration, green structure, and ecological linkage. To this end, the state should select a number of parks with solid industrial foundations, complete infrastructure, and high green levels from national and provincial industrial parks, further enhance the level of land conservation and intensive utilization, and promote the co-construction and sharing of infrastructure. At the park level, it is necessary to strengthen the recycling and utilization of waste heat, excess pressure, and waste heat resources, as well as the circular utilization of water resources. Build intelligent microgrids, promote waste resource exchange among park enterprises, complete the green chain of industries within the park, promote the construction of information and technology service platforms, encourage enterprises to develop green products, lead industries to create green factories, and establish green supply chains, in order to achieve overall green development of the park. This series of measures constitutes an industrial policy with ecological and environmental goals (Harrison et al., 2017) [16]. Compared with traditional industrial policies, the green industrial park policy aims to resolve the contradiction between economic growth and energy conservation and emission reduction, protect the ecological environment, and achieve environmental benefits. By combining traditional industrial parks with environmental policies, the green industrial park policy enriches the environmental governance framework and gradually attracts the attention of governments around the world (Altenburg and Rodrik, 2017) [1], becoming an important policy tool for environmental and low-carbon governance. With the implementation of the green industrial park policy and the diversification of policy types, more and more scholars have begun to study the impact of this policy, mainly focusing on environmental carbon emissions and socio-economic aspects.

Existing literature on green industrial park policies primarily focuses on two directions. On the one hand, some scholars concentrate on the relationship between green industrial park policies and socio-economic development, exploring the economic effects of low-carbon industrial park construction and conducting extensive empirical investigations into its innovation, structural, and environmental effects. Green and low-carbon transformation, as a crucial means to enhance industrial competitiveness and achieve the dual carbon goals, has become a trend in the development of industrial parks. However, some literature primarily analyzes low-carbon industrial parks through qualitative research. Although it examines the impact of eco-industrial demonstration park policies on socio-economic development, it fails to focus on the specific environmental impacts of low-carbon industrial parks.

On the other hand, relevant research has focused on the relationship between green and low-carbon park policies and environmental aspects such as carbon emissions. These studies discuss the reasons for the "quantity" growth of carbon emissions from the perspectives of economic output, population size, and urbanization process. Meanwhile, some scholars have empirically investigated the carbon emission reduction effects of factors such as technological progress (Ma et al., 2019), industrial structure (X. Liu et al., 2022) [25], and new urbanization (Wang and Wang, 2022) [38]. Furthermore, some scholars have attempted to depict the "quality" of carbon emissions through indicators such as carbon index (Ang, 1999) [2], per capita carbon emissions, and carbon productivity (Pan and Zhang, 2022) [32]]. Among them, carbon productivity, as an implicit factor input, is used to evaluate the economic benefits of an economy per unit of carbon resources. It not only considers the necessity of reducing the absolute amount of carbon emissions but also focuses on the importance of achieving environmentally sustainable economic growth. Relevant research indicates that technological innovation, per capita GDP, and the improvement of informatization level contribute to improving carbon productivity, while the level of urbanization and the proportion of industrial added value in GDP are negatively correlated with it.

It is noteworthy that the aforementioned literature often focuses solely on the impact of green and low-carbon industrial park policies, or merely explores their socio-economic impacts while neglecting environmental impacts. Alternatively, while paying attention to the environment, they analyze the "quality" and "quantity" impacts of carbon emissions in a fragmented manner. Few studies simultaneously explore the dual impacts of green regional policies on both the "quantity" and "quality" of carbon emissions.

Therefore, this paper regards the policy pilot of green industrial parks as a quasi-natural experiment, systematically evaluates the carbon emission reduction effect of low-carbon transformation in industrial parks by constructing a difference-in-differences (DID) model, and effectively mitigates endogeneity issues using the instrumental variable method. At the same time, within the framework of the DID method, a comprehensive investigation is conducted on the mechanism and heterogeneous effects of carbon emissions in low-carbon industrial park pilots (Jiang, 2022).

3. Theoretical mechanism

Industrial parks have become a significant force in leading regional innovation-driven and high-quality development (F. Liu et al., 2022), and there is an inseparable intrinsic connection between them and low-carbon development. Especially during the important historical stage of China's economic transition from high-speed growth to high-quality development, green industrial parks play a particularly crucial role in energy conservation and carbon reduction. On the one hand, green industrial parks set high standards and requirements for green development from the policy design level. Some green industrial parks use environmentally friendly materials in their construction, directly reducing carbon emissions (Ma et al., 2022). At the same time, multiple policy-leading demonstration areas are actively promoting green and smart parks, with "green energy and energy conservation and environmental protection" as one of the key development industries. This has played an important role in accelerating the manufacturing industry towards high-end, intelligent, and green development, which in turn directly promotes the improvement of carbon productivity.

On the other hand, the innovation-driven model guided by green industrial parks meets the requirements of energy conservation, carbon reduction, and sustainable development. As an important measure for building an innovative country, pilot projects of green industrial parks require green innovation to be the primary driving force for regional development. This helps shift production models from labor- and capital-intensive to knowledge- and technology-intensive, and transform economic development patterns from extensive ones characterized by high investment and high energy consumption to intensive ones with green development as the main theme.

Finally, green industrial parks facilitate the industrial agglomeration of green enterprises from different industries within a certain area. During this process, enterprises may generate "externalities." This agglomeration can lead to cross-industry knowledge spillovers, thereby promoting enterprise innovation and regional economic development (Zhou and Liu, 2020) [43]. Furthermore, this complementary division of labor system has the potential to effectively reduce expenses and conserve energy. It also promotes resource and technology exchanges between companies through knowledge dissemination. Some energy-based enterprises may develop technologies that enhance energy efficiency in the production process to save costs. These technologies are also passed on to other enterprises through the knowledge-sharing effect within the park, enabling enterprises within the entire park to use energy more efficiently, thus contributing to the "quantity reduction" of carbon emissions and the "quality improvement" of carbon productivity. Based on this, this paper proposes the following:

Hypothesis 1: The Green Industrial Park Policy (GIP) can achieve the dual effects of carbon emission reduction and carbon productivity improvement.

The aforementioned analysis delves into the multiple mechanisms through which Green Industrial Parks (GIPs) contribute to achieving carbon emission reduction and enhancing carbon productivity. We pay particular attention to the pathways of green innovation, energy efficiency improvement, and industrial agglomeration.

(1) The driving effect of green innovation on carbon emission performance:

Green innovation plays a crucial role in enhancing carbon emission performance, primarily through direct and indirect carbon emission reduction innovations. Specifically, direct carbon emission reduction innovations (such as carbon capture and storage technology) can directly reduce carbon emissions, thereby optimizing carbon emission performance. At the same time, green innovation may indirectly affect carbon emission performance through the following four mediating channels (see Figure 1). Firstly, green innovation can improve carbon emission performance by optimizing the structure of energy consumption. Green innovation has the potential to enhance energy utilization efficiency and promote the substitution of clean energy for fossil fuels, thereby improving carbon emission performance (Du et al., 2019). However, as China's energy structure is still dominated by coal, this improvement may not be significant (Xu et al., 2019). Secondly, green innovation can improve carbon emission performance by promoting industrial upgrading, shifting production from low value-added, high-pollution industries to high value-added, environmentally friendly industries, reducing the proportion of pollution-intensive industries in the economy. However, the energy rebound effect may offset some of the benefits, increasing the proportion of high-energy-consumption industries in the overall economy and thus reducing carbon emission performance (Du et al., 2021; Shao et al., 2019a, 2019b) [34][35]. Thirdly, green innovation can also affect carbon emission performance in the process of urbanization. Urbanization can either inhibit the emission reduction effect of green innovation through increased energy consumption and carbon emissions, or promote the carbon emission reduction effect of green innovation through economies of scale (Liu et al., 2021; Shao et al., 2019b). Fourthly, green innovation can also affect carbon emission performance by attracting foreign direct investment (FDI). On the one hand, there may be a substitution relationship between local green technologies and green technologies introduced through FDI (Grey and Brank,

2002) [13]. On the other hand, the promotion of green innovation may change the competitive advantage of foreign enterprises in the host country (Cole et al., 2010) [5].

Hypothesis 2: Green Industrial Parks (GIPs) may promote carbon emission reduction and enhance carbon productivity through four mediating effects: promoting green innovation in energy consumption structure, industrial structure, urbanization, and foreign direct investment.

(2) Dual impacts of energy efficiency improvement and carbon emission reduction:

Fossil energy consumption is one of the main driving forces of carbon emissions (Li et al., 2021; Yasmeen et al., 2020) [41]. Therefore, optimizing energy consumption structure (Ma et al., 2020; Yang et al., 2020) [40] and improving energy efficiency (Pei et al., 2021) [33] are important paths to reduce carbon emissions. Given the economic growth, technical challenges in clean energy development, and high-cost pressures, China's energy structure dominated by fossil fuels is difficult to transform in the short term (Brathwaite et al., 2010) [3]. Hence, improving energy efficiency is considered a more effective way to achieve a low-carbon economy (Cai et al., 2019; Farla and Blok, 2000) [9] ;(Nibedita and Irfan, 2021) [30].

However, William Stanley Jevons pointed out in "The Coal Question" that improving coal utilization efficiency may actually increase coal consumption. Specifically, the energy saved through improved energy efficiency may be partially or fully offset by new energy demand generated by micro-substitution effects, income effects, output effects of economic agents, as well as macro-secondary effects, conversion effects, spillover effects, etc., making the energy-saving effect of energy efficiency policies often smaller than expected (Freire-González and Puig-Ventosa, 2015; Greening et al., 2000) [10]. This led to the proposal of the "Jevons's paradox" or "green paradox" (Van Der Ploeg and Withagen, 2013) [37]. To explain this phenomenon, scholars have introduced the concept of the energy rebound effect, which means that any expected energy saved through improving energy efficiency may be partially or fully offset, or even exceeded, by demand growth (Ouyang et al., 2018) [31]. Therefore, improving energy efficiency may have a dual impact, and whether it can effectively reduce carbon emissions remains to be further studied (F. Liu et al., 2022).

Hypothesis 3: Green Industrial Parks (GIPs) may achieve carbon emission reduction and improvement in carbon productivity by enhancing energy utilization efficiency.

(3) Dynamic effects of industrial agglomeration and carbon emissions:

Industrial agglomeration refers to a highly concentrated group of interconnected enterprises formed within a specific geographical area. Marshall believed that agglomeration could generate "externalities"; Jacobs pointed out that diversified agglomeration promotes regional economic development and corporate innovation through cross-industry knowledge spillovers. Furthermore, this complementary division of labor system can effectively reduce costs, conserve energy, and facilitate the exchange of resources and technology through knowledge dissemination, thereby fostering the emergence of new clean technologies and reducing environmental pollution (Van der Ploeg & Withagen, 2013).

In industrial parks, the significant forward and backward linkages as well as supply-demand relationships between manufacturing and productive service industries make them ideal subjects for studying industrial collaborative agglomeration (Ma et al., 2020). The impact of industrial collaborative agglomeration on carbon emissions is divided into positive and negative externalities. In the initial adjustment phase, enterprises share knowledge by integrating upstream and downstream industrial chains. However, due to slow knowledge exchange, issues such as increased carbon emissions and decreased carbon productivity may become more prominent. In the mature stage, the support of the service industry effectively improves overall production efficiency, forming a resource-saving, low-carbon circular production model, thereby reducing carbon emission intensity and increasing carbon productivity. The specific principles are illustrated in Figures (1) and (2).Therefore, this paper proposes：

Hypothesis 4: Green industrial parks may affect carbon emission intensity by enhancing the collaborative agglomeration of manufacturing and productive service industries.

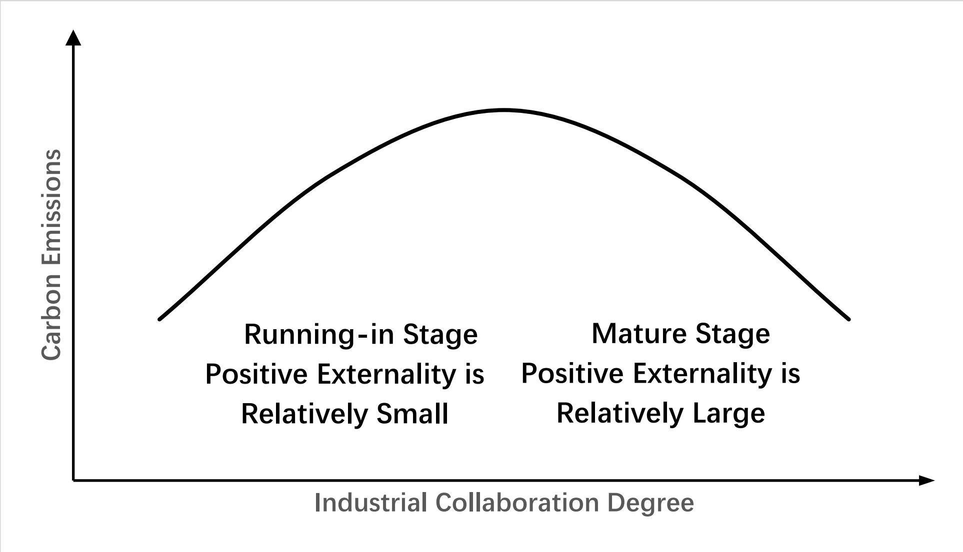

Figure (1): Dynamic Effects of Industrial Agglomeration on Carbon Emissions

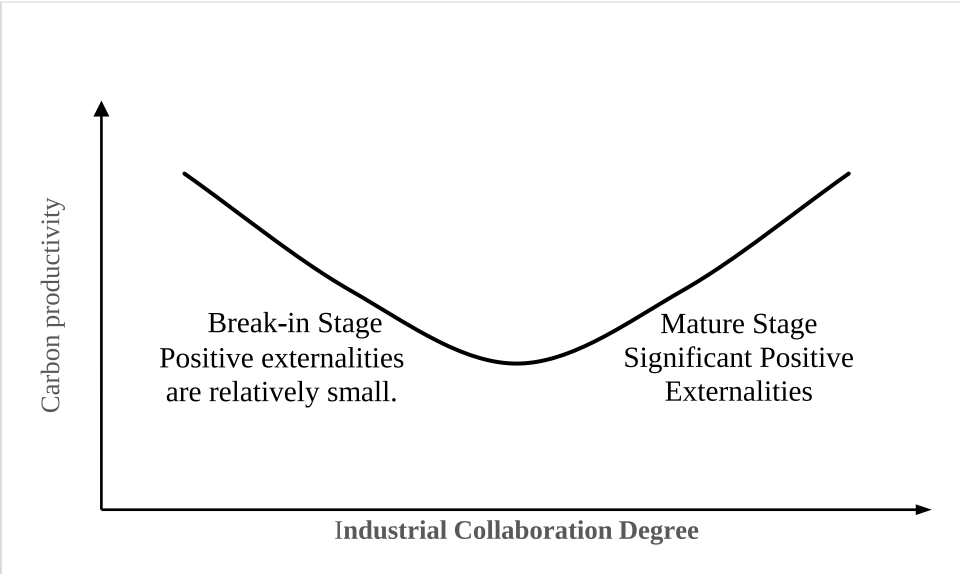

Figure (2): Dynamic effects of industrial agglomeration on carbon productivity

4. Methodology and Data

4.1. DID model

We employ the Difference-in-Differences (DID) method to examine the dual impact of green industrial park policies on carbon emissions. Green industrial park policies lead to changes in two dimensions of carbon emissions and carbon productivity: changes before and after policy implementation, as well as differences between cities with and without policies. The DID model is as follows:

$$LC_{it} = \alpha_0 + \alpha_1 GIP_{it} + \lambda_j \sum_{j=1}^{J} Z_{it,j} + u_i + v_t + \epsilon_{it} \tag{1}$$

$$LCP_{it} = \alpha_0 + \alpha_1 GIP_{it} + \lambda_j \sum_{j=1}^{J} Z_{it,j} + u_i + v_t + \epsilon_{it} \tag{2}$$

In equation (1), LC represents the dependent variable, carbon emissions, and LC_{it} denotes the logarithm of carbon emissions in city i in year t. Z_{it} stands for a series of control variables, including urban economic development level, urban construction level, population density, financial development level, and openness. u_i signifies a set of city-specific dummy variables, while v_t represents a set of year-specific dummy variables, accounting for the fixed effects of both cities and years. ϵ_{it} represents the random error term.

The only difference between equation (2) and equation (1) lies in the explained variable. The explained variable in equation (2) is the log carbon productivity (LCP), where LCP_{it} represents the log carbon productivity of city i in year t. The explanatory variables and control variables are the same as in equation (1).

4.2. SDID model

Given the potential spatial influencing factors of green industrial park policies on the "quantity" and "quality" of urban carbon emissions, we further designed the following SDID model

$$LC_{it} = \sum_{i=1}^{n} \sigma W_{it} LC_{it} + \alpha_0 + \alpha_1 GIP_{it} + \lambda_j \sum_{j=1}^{J} Z_{it,j} + \beta_1 \sum_{i=1}^{n} W_{it} GIP_{it} + \pi_j \sum_{j=1}^{J} \sum_{i=1}^{n} W_{it} Z_{it,j} + \epsilon_{it} \tag{3}$$

$$LCP_{it} = \sum_{i=1}^{n} \sigma W_{it} LC_{it} + \alpha_0 + \alpha_1 GIP_{it} + \lambda_j \sum_{j=1}^{J} Z_{it,j} + \beta_1 \sum_{i=1}^{n} W_{it} GIP_{it} + \pi_j \sum_{j=1}^{J} \sum_{i=1}^{n} W_{it} Z_{it,j} + \epsilon_{it} \tag{4}$$

Where σ is the spatial correlation coefficient; W is the spatial weight matrix, $W = 1/d_{ij}^2$, and d_{ij}^2 represents the distance between city i and city j in terms of longitude and latitude, and W is row-normalized. The remaining variables are the same as in Equations (1) and (2). Compared to the DID model, the SDID model can describe the spatial impact of the implementation of green industrial park policies in local cities on the "quantity" and "quality" of carbon emissions in neighboring cities.

4.3. Variables and Data

We utilized panel data from 277 prefecture-level cities in China spanning from 2010 to 2021 as our research sample. The subsequent section delineates the variables and their respective data sources.

4.3.1. Dependent variable

To measure the "quantity" and "quality" of carbon emissions, we select the logarithm of carbon emissions and carbon productivity as dependent variables. The logarithm of the total urban carbon emissions (LC) serves as the measurement standard for the "quantity" of carbon emissions. The carbon emission data is sourced from the China Emissions Accounting Database (CEADS) for prefecture-level cities. For prefecture-level cities with a large number of missing values, we use the corresponding county-level data from the CEADS and aggregate them to fill the gaps. Considering the significant differences in the raw data of carbon emissions and carbon productivity across different regions, we take the logarithms of both to mitigate the interference of bias factors. We select carbon productivity (LCP) as the measurement standard for the "quality" of carbon emissions. Carbon productivity (LCP) is measured by dividing actual GDP by carbon emissions (LC).

4.3.2. Independent variable

The independent variable is the Green Industrial Park Policy, which is a policy dummy variable taking a value of 1 or 0. GIP=1 indicates that city i implemented the Green Industrial Park Policy in year t and belongs to the treatment group; GIP=0 indicates that city i did not implement the Green Industrial Park Policy in year t and belongs to the control group. Some cities gradually implemented the Green Industrial Park Policy after 2017. The key areas of the Green Industrial Park Policy are Beijing-Tianjin-Hebei, Yangtze River Delta, and Pearl River Delta. The specific goal of this policy is to continuously improve the green manufacturing and service system, promote green industrial development, and assist the industrial sector in achieving carbon peak and carbon neutrality. We set the cities that implemented the Green Industrial Park Policy as the treatment group and those that did not as the control group. The cities that implemented the Green Industrial Park Policy are listed in the supplementary document of Appendix A. There are a total of 116 cities in the treatment group and 161 cities in the control group.

4.3.3. Control variables

Based on previous theoretical analysis and existing research, we introduced a set of control variables into the model to reduce potential biases caused by omitted variables. The control variables are as follows:

Economic development level (GDP): It is closely related to carbon emissions (LC) and carbon productivity (LCP) (Grossman and Krueger, 1995) [14]. The level of urban economic development is measured by per capita GDP (PGDP).

Urbanization Level (UL): Generally speaking, a higher urbanization level leads to more carbon emissions. The urbanization level is measured by the ratio of urban construction land area to administrative land area

Population Density (PD): A higher population density may lead to increased carbon emissions. Population density is measured by the ratio of permanent residents to administrative land area at the prefecture-level city level.

Openness (OPEN): It is measured by the proportion of actual utilized foreign capital to GDP, converted into RMB using the average exchange rate of the current year. Foreign direct investment introduces advanced production technology or advanced management theories and experiences, affecting carbon emissions (LC) and carbon productivity (LCP).

Financial development level (FINA): It is measured by taking the logarithm of the sum of the balance of various RMB loans and deposits of financial institutions at the end of the year. The level of financial development affects the resource allocation and productivity of the production sector. A developed financial market can reduce the financial risks of industrial enterprises, improve their financing capabilities, effectively stimulate technological innovation, and reduce energy consumption and pollution emissions in the production process of industrial enterprises, thereby affecting carbon emissions (LC) and carbon productivity (LCP)

4.3.4. Mechanism variables

Based on the analysis of the impact mechanism of carbon emissions, this paper selects energy utilization efficiency, innovation level, and industrial agglomeration level, which are closely related to carbon emissions, as mechanism variables.

Energy efficiency (EE), referring to the method described by Shi Dan (2006), is represented by the actual GDP generated per unit of energy consumption. As an important indicator reflecting the internal structure of energy consumption, energy efficiency and energy structure adjustment are crucial means to achieve carbon emission reduction, especially implementing proactive energy efficiency measures as the most effective way to reduce emissions. Therefore, energy efficiency is selected as one of the mechanism variables.

Innovation level (INNO) is measured by selecting the innovation index of each city (Kou Zonglai, Liu Xueyue, n.d.). According to the long-term fluctuation theory, innovation plays a crucial role in the changes of the economic system (Fusari and Reati, 2013). Higher levels of innovation promote carbon emissions (LC). By developing green technologies and product research and development, enterprises produce differentiated high-value-added products, enhancing the market competitiveness of enterprises and products, and gradually eliminating high-energy consumption and high-pollution enterprises. This reduces carbon emissions, and innovation capabilities help enterprises obtain government subsidies and other support, indirectly reducing costs and having a positive impact on reducing carbon emissions (LC). Therefore, we select the city innovation index as one of the mechanism variables.

The level of industrial agglomeration (AGG) is measured using location entropy. Industrial agglomeration enables enterprises to create competitive effects and reduce costs (including energy consumption), which in turn creates effective incentives for energy conservation and emission reduction. (Shi and Shen, 2013) [36]; (Han et al., 2018). According to the agglomeration life cycle model, when industrial agglomeration is in the formation and development stages, positive externalities of agglomeration begin to emerge, which is conducive to reducing carbon emissions and improving carbon productivity. Drawing on previous practices (Fan and Scott, 2003) [8]; (Liu and Sheng, 2016) [24]; (Ji and Liu, 2018) [18], this study uses location entropy to measure the level of industrial agglomeration. The calculation formula for the level of industrial agglomeration is as follows:

$$AGG_{it} = \frac{ys_{it}/Ys_t}{GDP_{it}/GDP_t} \tag{5}$$

In Equation 5, AGG_{it} represents the location entropy of city i in year t, ys_{it} represents the industrial output value of city *i* in year *t*, Ys_t represents the national industrial output value in year t, GDP_{it} represents the urban GDP of city i in year t, and GDP_t represents the national GDP in year t.

The data for the aforementioned variables are sourced from the "China City Statistical Yearbook" and the "China Statistical Yearbook". Table 4.3.4 provides descriptive statistics for the main variables.

Table 4.3.4 Descriptive statistics of dependent variables

	(1)	(2)	(3)	(4)	(5)
Variable	Obs	Mean	Std. dev.	Min	Max
LC	3,324	3.068577	1.167732	-3.489457	6.126338
LCP	3,324	4.343571	1.312455	0.5836311	12.64213
GIP	3,324	0.111312	0.314565	0	1
OPEN	3,324	0.035741	0.09917	0	1.606002
UL	3,324	0.018805	0.042647	0.0000301	0.868982
PGDP	3,324	10.70752	0.567871	8.628198	12.29279
FINA	3,324	17.42738	1.11617	14.38273	21.74637
PD	3,324	5.757754	0.958539	1.707661	9.066794
EE	3,324	0.018585	0.010819	0.0030255	0.163955
AGG	3,324	1.021928	0.22804	0.0000714	1.845915
INNO	3,324	25.79351	116.6838	0.011343	2907.851

5. Empirical Results

5.1. Baseline regression results

We utilize the DID model to estimate the dual impact of green industrial park policies on urban carbon emission reduction. The regression results of green industrial park policies on carbon emissions and carbon productivity are presented in Table 4.1. Columns (1) and (2) show the baseline regression of green industrial parks on urban carbon emissions. For equation (1), we start with the simplest specification, controlling only for fixed effects of year and city. The results are reported in column (1). Furthermore, in column (2), we control for a series of variables, including financial development level (FINA), urban development level (GDP), urban construction level (UL), openness level (OPEN), and population density (PD). Both the GIP coefficients in columns (1) and (2) are negative and significant at the 1% level. This indicates that green industrial park policies have reduced the level of urban carbon emissions.

Columns (3) and (4) report the baseline regression of green industrial parks on urban carbon productivity. The coefficients of GIP are all significant and positive, indicating that the green industrial park policy has reduced urban carbon emission levels while simultaneously improving carbon productivity. The implementation of the green industrial park policy has encouraged adjustments to the industrial structure and upgrades in pollution control technology. This has driven technological progress and the use of green energy, thereby enhancing carbon productivity.

Table 5.1: Benchmark regression results

	(1)	(2)	(3)	(4)
	lc	lc	LCP	LCP
GIP	-0.296	-0.282	0.379	0.346
	(0.0685)	(0.0685)	(0.0688)	(0.0687)
PGDP		0.250		0.397
		(0.115)		(0.116)
UL		0.378		-0.567
		(0.751)		(0.753)
PD		-0.452		0.486
		(0.0938)		(0.0941)
OPEN		-0.455		0.327
		(0.286)		(0.287)
FINA		0.291		-0.0872
		(0.148)		(0.148)
_cons	3.199	-1.603	3.689	-1.717
	(0.0547)	(2.439)	(0.0549)	(2.446)
Fixed year	Yes	Yes	Yes	Yes
Fixed city	Yes	Yes	Yes	Yes
N	3324	3324	3324	3324
R^2	0.230	0.239	0.341	0.349

Standard error sinparentheses
p<0.1,p<0.05,p<0.01

5.2. Robustness test

5.2.1. Parallel Trend Test

To assess whether there are biases in the benchmark regression results, we employ the event study method for parallel trends testing, comparing the carbon emissions (LC) and carbon productivity (LCP) of the treatment group cities and the control group cities. If there is a difference in the trend of change between the treatment group and the control group before the event, this indicates that the differences in carbon emissions (LC) and carbon productivity (LCP) may not be caused by the green industrial park policy, but rather due to systematic differences between the two groups before the event. Figure 5.2.1(1) shows that there was no significant difference in carbon emissions (LC) between the treatment group and the control group before the policy implementation. This meets the requirement of the DID model, indicating that there is no systematic difference in the trend of carbon emissions (LC) between the two groups. Figure 5.2.1(2) shows that there was also no significant difference in carbon productivity (LCP) between the treatment group and the control group before the policy implementation.

From Figure 5.2.1(1) and Figure 5.2.1(2), it can be observed that starting from the first year after the implementation of the green industrial park policy, the reduction rate of carbon emissions (LC) in the treatment group is significantly faster than that in the control group. At the same time, the increase rate of carbon productivity in the treatment group is significantly higher than that in the control group. Therefore, the DID model used in this study conforms to the parallel trend’s assumption.

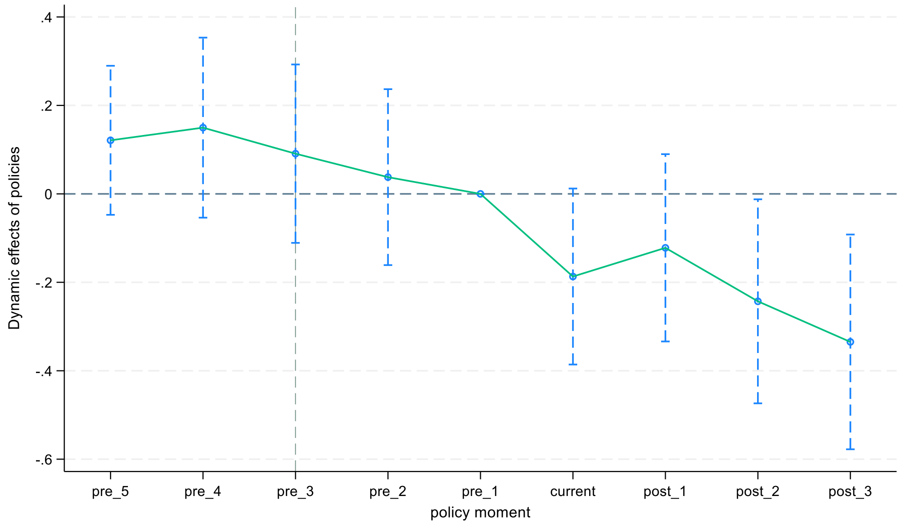

Figure 5.2.1 (1) Parallel Trend Test for Carbon Emissions

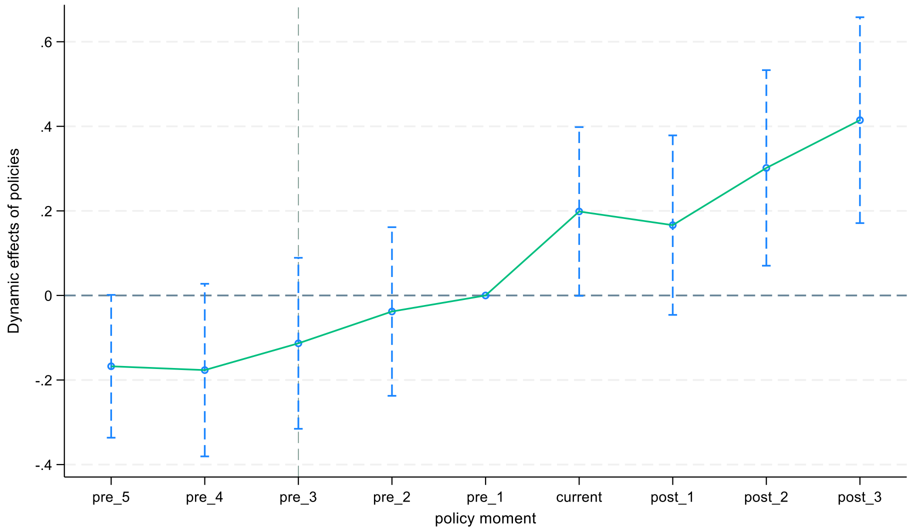

Figure 5.2.1 (2) Parallel trend test of carbon productivity

5.2.2. Placebo test

We drew inspiration from the research conducted by LaFerrara et al. (2012) to randomly generate a list of cities implementing green industrial park policies, and assigned a random year for the implementation of these policies to these cities between 2010 and 2021. This allowed us to construct a "pseudo" GIP variable based on the randomly assigned treatment group and the randomly determined year of policy implementation. Subsequently, we conducted regressions in Equations (1) and (2), substituting the actual GIP variable with the "pseudo" GIP. To ensure consistent results, we repeated this randomization process 500 times. The probability density distribution of the estimated coefficients for the "pseudo" GIP dummy variable in carbon emissions is illustrated in Figure 5.2.2(1), and the distribution for carbon productivity is depicted in Figure 5.2.2(2). These estimated coefficients exhibit a distribution centered around a normal function with a mean of 0, which contrasts with the results obtained using the actual GIP dummy variable (as shown in (1) and (2) in 5.1). The placebo test further confirmed that our findings were not coincidental.

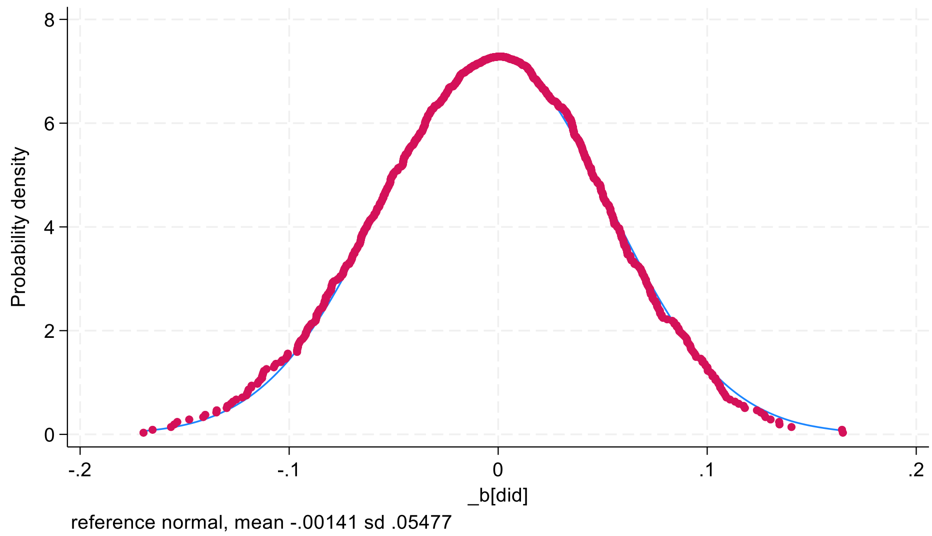

Figure 5.2.2 (1): Estimated coefficients of the "false" GIP dummy variable in carbon emissions

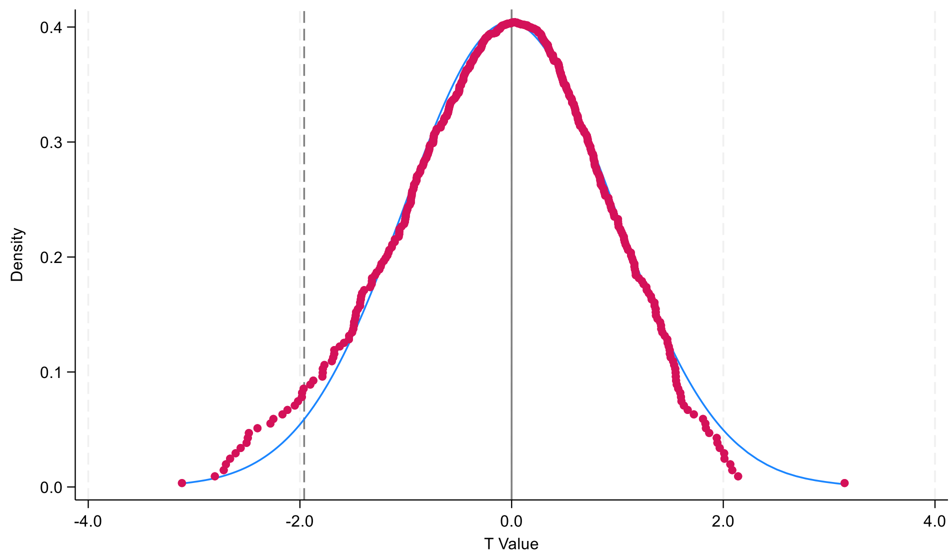

Figure 5.2.2 (2) Estimated coefficients of the "false" GIP dummy variable in carbon productivity

5.2.3. Endogeneity test

①Instrumental variable method

We selected data on the opening of railways during the Republic of China era, sourced from "A Handbook of Chinese Railways" and "A Handbook of Chinese Railways". Following the practices outlined in (Tian Kun et al., 2023) and (Zhang Yuan and Liu Xiuyan, 2008), we labeled sample cities as either 1 or 0 based on whether they had railway transportation conditions in 1933. The implementation of railways during the Republic of China era indicates that the local economic conditions may be better or the city's strategic position may be higher, which may positively influence the likelihood of implementing green industrial park policies. However, the data on the opening of railways during the Republic of China era does not affect urban carbon emissions or carbon productivity, satisfying the condition of exogenousness. Since whether the railways were opened in 1933 was fixed and did not change over time, we selected the logarithm of the interaction term between the data on the opening of railways during the Republic of China era and the year as an instrumental variable.

Columns (1) and (3) in Table 5.2.3（1） represent the corresponding empirical test results. The estimated coefficient of GIP remains significantly positive, indicating that the results of the benchmark regression are robust. In addition, we conducted a non-identification test using the LM statistic proposed by Kleibergen and Paap (2006), and the results showed that IV rejected the null hypothesis of "instrument unidentifiable" at the 1% level. Meanwhile, the weak identification test based on the Kleibergen-Paap Wald F statistic also indicated that, in the case of only one endogenous variable, the value of the statistic was greater than the critical value at the 10% level, as proposed by Stock and Zimering (2005). Therefore, we can strongly reject the null hypothesis that IV is a "weak instrument variable".

Table 5.2.3（1） Instrumental variable regression results

	(1)	(2)	(3)	(4)
	firstGIP	second	firstGIP	second
VARIABLES	GIP	LC	GIP	LCP
GIP		-4.1886		3.4412
		(-5.94)		(5.89)
IV	73.9259		73.9259	
	(6.67)		(6.67)	
PGDP	0.0693	0.4894	0.0693	-0.0522
	(1.60)	(2.20)	(1.60)	(-0.27)
UL	-0.7144	-3.7270	-0.7144	2.5621
	(-3.49)	(-2.57)	(-3.49)	(2.09)
PD	0.0386	0.1826	0.0386	-0.0600
	(2.38)	(2.13)	(2.38)	(-0.82)
OPEN	-0.1145	-0.2149	-0.1145	0.3393
	(-1.24)	(-0.50)	(-1.24)	(0.80)
FINA	0.0418	0.4734	0.0418	0.1404
	(2.27)	(4.47)	(2.27)	(1.56)
Kleibergen-Paaprk LM statistic	29.437		29.437	
Chi-sq(1)P-val	0.0000		0.0000	
CrAGG-Donald Wald F statistic	167.568		167.568	
Kleibergen-Paaprk Wald F statistic	44.466		44.466	
10%maximal IV size	16.38		16.38	
Constant	564.0553	-10.9397	-564.0553	2.4386
	(-6.69)	(-4.66)	(-6.69)	(1.19)
ObservatioEW	1,080	1,080	1,080	1,080
R-squared	0.135	-0.411	0.135	-0.004

Robustt-statisticsinparentheses

p<0.01,p<0.05,p<0.1

②Replace the dependent variable

Based on previous practices, we replaced the dependent variable with the initial values of carbon emissions and carbon productivity (without taking logarithms) and conducted regression analysis. The regression results are listed in Table 5.2.3, and it can be seen that the coefficient of GIP remains significant.

Table 5.2.3（2） Replacement of dependent variables

	(1)	(2)	(3)	(4)
	CO2	CO2	CP	CP
GIP	-6.247	-5.690	1989.0	1908.2
	(2.032)	(2.039)	(595.8)	(598.1)
PGDP		4.257		-1687.3
		(3.430)		(1006.4)
UL		35.92		-465.1
		(22.34)		(6553.4)
PD		-8.795		2405.5
		(2.792)		(819.1)
OPEN		-14.72		648.8
		(8.515)		(2498.3)
FINA		-0.878		-480.9
		(4.390)		(1288.0)
_cons	36.37	58.35	80.41	11504.7
	(1.623)	(72.57)	(475.9)	(21291.2)
Fixed year	Yes	Yes	Yes	Yes
Fixed city	Yes	Yes	Yes	Yes
N	3324	3324	3324	3324
R^2	0.083	0.088	0.038	0.042

Standard errors in parentheses

$p<0.1, p<0.05, p<0.01$

5.2.4. Eliminate the impact of other environmental policies

In addition to the green industrial park policy, carbon emissions (LC) and carbon productivity (LCP) are also influenced by other policies. For example, cities that have implemented the national new industrialization industry demonstration base policy can promote technological innovation and clean production. Cities that have implemented this policy will vigorously support enterprises in introducing and developing advanced energy-saving and emission-reduction technologies, such as efficient energy utilization technologies, clean production processes, and pollution control technologies, to reduce energy consumption and carbon dioxide emissions. Simultaneously, implementing this policy can optimize the industrial structure, encourage the development of high-tech industries and modern service industries with high added value and low energy consumption, gradually eliminate backward production capacities with high energy consumption and high pollution, adjust and optimize the industrial structure, reduce the overall carbon emission level, and improve carbon productivity. Finally, prefecture-level cities that implement this policy can also strengthen energy management and utilization, encourage enterprises to implement energy management systems, enhance monitoring and control of energy use, improve energy utilization efficiency, reduce energy waste, and thereby reduce carbon emissions.

Among the cities implementing the green industrial park policy, 25 cities implemented the national new industrialization industry demonstration base policy from 2017 to 2021. We excluded these 25 cities and then re-estimated using equations (1) and (2). The results of carbon emissions are reported in columns (1) and (2) of Table 5.2.4, and the results of carbon emissions are reported in columns (3) and (4) of Table 5.2.4. The results show that the regression coefficient of GIP is still significantly positive, indicating that the results remain robust after controlling for the national new industrialization industry demonstration base policy.

Table 5.2.4 Elimination of the influence of other variables

	(1)	(2)	(3)	(4)
	LC	LC	LCP	LCP
GIP	-0.304	-0.290	0.387	0.354
	(0.0733)	(0.0733)	(0.0735)	(0.0734)
PGDP		0.221		0.421
		(0.120)		(0.120)
UL		0.737		-1.027
		(0.961)		(0.963)
PD		-0.463		0.496
		(0.0988)		(0.0989)
OPEN		-0.455		0.323
		(0.289)		(0.290)
FINA		0.302		-0.104
		(0.152)		(0.152)
Fixed year	Yes	Yes	Yes	Yes
Fixed city	Yes	Yes	Yes	Yes
_cons	3.211	-1.418	3.628	-1.770
	(0.0576)	(2.515)	(0.0578)	(2.518)
N	3024	3024	3024	3024
R^2	0.227	0.236	0.337	0.346

Standard errors in parentheses

$p<0.1$,$p<0.05$,$p<0.01$

6. Further analysis

6.1. Spatial regression analysis

6.1.1. Moran's index

Before conducting the SDID model, we used the global Moran's I index to perform a spatial autocorrelation analysis on carbon emissions (LC) and carbon productivity (LCP). The global Moran's I index value for carbon emissions (LC) is presented in Table 6.1.1(1). From 2010 to 2021, the Moran's I index for both carbon emissions (LC) and carbon productivity was mostly significantly positive. This indicates that the spatial distribution of carbon emissions (LC) across cities is not completely independent, and there is a significant positive spatial spillover effect between cities in terms of carbon emissions (LC). The carbon emissions (LC) of neighboring cities affect the carbon emissions (LC) of adjacent cities.

Table 6.1.1 (1) Moran's I index of carbon emissions

Variables	I	E(I)	sd(I)	z	p-value
LC2010	0.063	-0.004	0.031	2.165	0.015
LC2011	0.034	-0.004	0.031	1.233	0.109
LC2012	0.105	-0.004	0.031	3.541	0
LC2013	0.155	-0.004	0.031	5.191	0
LC2014	0.151	-0.004	0.031	5.044	0
LC2015	0.128	-0.004	0.031	4.297	0
LC2016	0.17	-0.004	0.031	5.672	0
LC2017	0.165	-0.004	0.031	5.518	0
LC2018	0.113	-0.004	0.03	3.837	0
LC2019	0.087	-0.004	0.03	2.988	0.001
LC2020	0.078	-0.004	0.031	2.683	0.004
LC2021	0.059	-0.004	0.031	2.05	0.02

The global Moran's I index values for carbon emission rate (LCP) are presented in Table 5.1.1 (2). Between 2010 and 2021, the Moran's I index for carbon productivity (LC) was significantly positive. This indicates that the spatial distribution of carbon productivity (LCP) across cities is not completely independent, and there is a significant positive spatial spillover effect between cities in terms of carbon productivity (LCP). The productivity (LCP) of neighboring cities affects the carbon productivity (LCP) of adjacent cities. This underscores the need to study the spatial effects of carbon emissions and productivity. We use the SDID model to estimate the spatial spillover effects.

Table 6.1.1 (2) Moran's I index of carbon productivity

Variables	I	E(I)	sd(I)	z	p-value
LCP2010	0.065	-0.004	0.031	2.239	0.013
LCP2011	0.096	-0.004	0.031	3.244	0.001
LCP2012	0.237	-0.004	0.031	7.853	0
LCP2013	0.257	-0.004	0.031	8.5	0
LCP2014	0.216	-0.004	0.031	7.167	0
LCP2015	0.255	-0.004	0.031	8.44	0
LCP2016	0.247	-0.004	0.031	8.185	0
LCP2017	0.204	-0.004	0.031	6.764	0
LCP2018	0.289	-0.004	0.031	9.536	0
LCP2019	0.12	-0.004	0.03	4.074	0
LCP2020	0.15	-0.004	0.031	5.028	0
LCP2021	0.13	-0.004	0.031	4.372	0

Similarly, we utilize Was the spatial weight matrix to plot the local Moran scatterplot for carbon emissions (as shown in Figure 6.1.1(1)) and the local Moran scatterplot for carbon productivity (as shown in Figure 6.1.1(2)), revealing the spatial differences in carbon emissions and carbon productivity across different cities. In Figure 6.1.1(1), the horizontal axis represents carbon emissions, while the vertical axis represents the spatial lag values of carbon emissions. In Figure 6.1.1(2), the horizontal axis represents carbon productivity, and the vertical axis represents the spatial lag values of carbon productivity. It is not difficult to observe that most cities are located in the first and third quadrants, indicating that carbon emissions and carbon productivity exhibit high-high and low-low spatial agglomeration characteristics. Cities in the second and fourth quadrants exhibit spatial distribution patterns of low-high and high-low for carbon emissions and carbon productivity. The sample fitting lines in the figure run through one or three quadrants, indicating that the overall carbon emissions and carbon productivity of cities have significant positive spatial autocorrelation

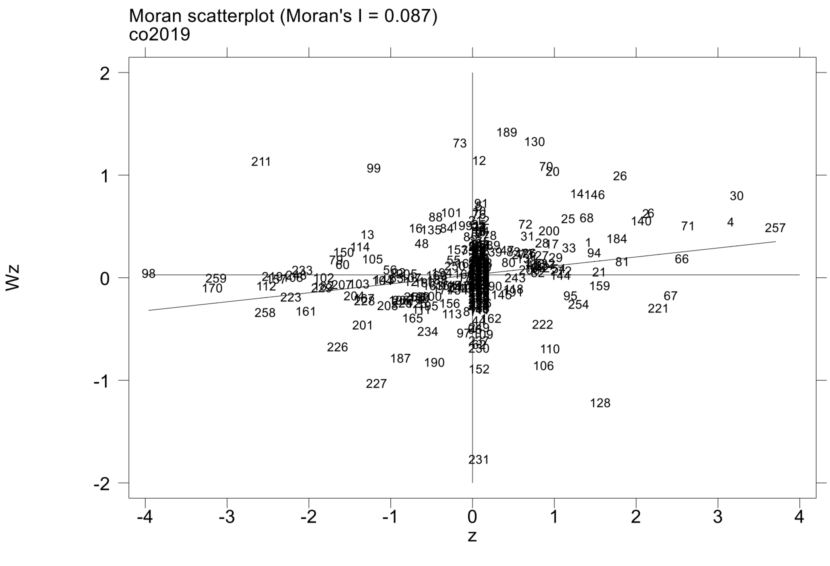

Figure 6.1.1 (1): Local Moran Scatter Plot of Carbon Emissions

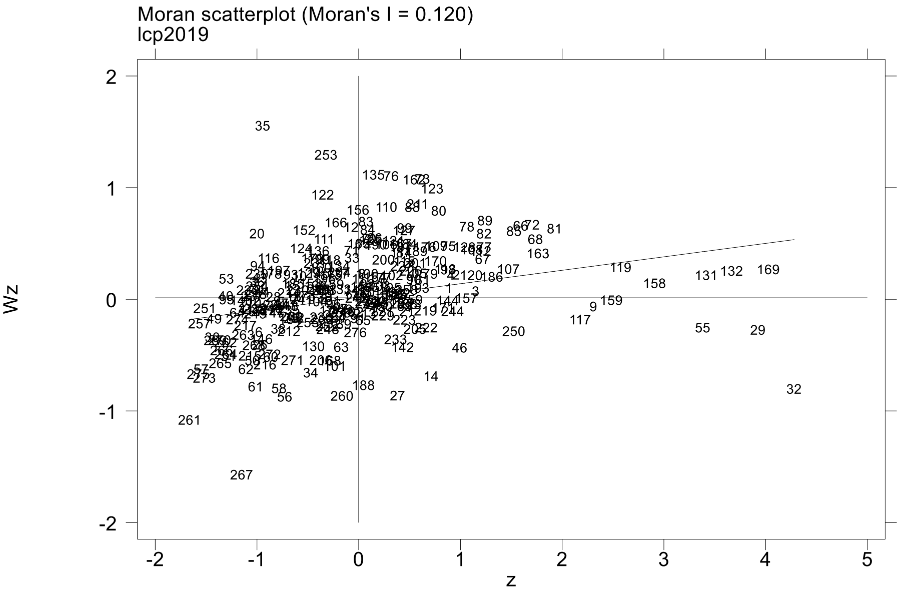

Figure 6.1.1 (2): Local Moran Scatterplot of Carbon Productivity

6.1.2. SDID model results

The regression results of the SDID model are presented in Table 6.1.2(3). The coefficients of GIP (Green Industrial Park Policy) in columns (1) and (2) of Table 6.1.2(3) are both significantly negative, indicating that the green industrial park policy reduces the LC (carbon emissions) of local cities. In local cities, the implementation of the green industrial park policy utilizes greener production technologies and more advanced scientific technologies, reducing non-green energy consumption in the production process and thus reducing carbon emissions.

In Table 6.1(3), the coefficients of GIP (Green Industrial Park Policy) in columns (3) and (4) are both significantly positive, indicating that the Green Industrial Park Policy has improved the local city's LCP (Carbon Productivity). The implementation of GIP in the local city brings progress in capital, technology, and information, thereby promoting the city's carbon productivity (LCP). In Table 6.1(3), the coefficients of W*LC in columns (1) and (2) are negative and significant, while the WLCP coefficients in columns (3) and (4) are negative but not significant, indicating that the Green Industrial Park Policy has no significant spatial spillover effect on the carbon productivity (LCP) of neighboring cities. There may be significant differences in technological capabilities between neighboring cities and cities with Green Industrial Parks. Some Green Parks may possess higher technological innovation, allowing them to reduce carbon emissions while simultaneously increasing the carbon emission rate, while neighboring cities cannot replicate these technologies and can only reduce carbon emissions through less advanced methods, which, however, cannot improve carbon productivity.

It is noteworthy that, when considering spatial effects as control variables, the direct effect of financial development level (FINA) on carbon emissions is significantly positive, while the spatial spillover effect is significantly negative. This implies that FINA has a positive impact on the carbon emissions (LC) of local cities, but a negative impact on the carbon emissions (LC) of neighboring cities. Higher levels of financial development promote urban economic growth, bringing greater economic benefits to urban development but also increasing urban carbon emissions. Additionally, a higher level of financial development exerts a siphon effect on enterprises in neighboring cities, absorbing various resources from these cities and thereby reducing their carbon emissions (LC) growth to some extent.

Table 6.1.1(3). Results of the SDID Model

	(1)	(2)	(3)	(4)
	LC	LC	LCP	LCP
Main				
GIP	-0.208	-0.200	0.252	0.228
	(0.0876)	(0.0888)	(0.0893)	(0.0900)
PGDP		0.297		0.0514
		(0.149)		(0.148)
UL		0.338		-0.430
		(0.469)		(0.485)
PD		-0.301		0.323
		(0.159)		(0.160)
OPEN		-0.198		0.119
		(0.258)		(0.276)
FINA		0.322		-0.232
		(0.144)		(0.143)
Wx				
GIP	-0.573	-0.616	0.729	0.602
	(0.127)	(0.145)	(0.145)	(0.144)
W*(LC/LCP)	-0.103	-0.104	-0.0720	-0.109
	(0.0616)	(0.0665)	(0.0577)	(0.0701)
PGDP		0.109		-0.109
		(0.291)		(0.281)
UL		1.705		-1.910
		(1.636)		(1.678)
PD		0.323		-0.312
		(0.255)		(0.253)
OPEN		0.241		-0.610
		(0.948)		(0.922)
FINA		-0.554		0.445
		(0.227)		(0.225)
Spatial				
rho	0.432	0.424	0.431	0.416
	(0.0314)	(0.0314)	(0.0309)	(0.0314)
Variance				
sigma2_e	0.674	0.667	0.677	0.672
	(0.0526)	(0.0515)	(0.0521)	(0.0510)
N	3324	3324	3324	3324
R^2	0.343	0.326	0.466	0.402

Standard errors in parentheses

$p<0.1$,$p<0.05$,$p<0.01$

6.2. Heterogeneity analysis

6.2.1. Resource-based heterogeneity

Resource-based cities refer to those where the dominant industries are typically engaged in the extraction and processing of natural resources such as minerals and forests. These resource-rich cities have made significant contributions to China's economic development. However, the gradual depletion of natural resources and the increasingly prominent pollution issues caused by these resources mean that resource-based cities face the risk of the "resource curse" and the pressure of industrial transformation. This raises the question of whether green industrial park policies promote the green economic development of resource-based cities or limit the quality of their economic development. Therefore, we set a dummy variable (RB) for city type. If city i is a resource-based city, then RB=1; otherwise, RB=0. We constructed a Difference-in-Differences-in-Differences (DDD) model to test the heterogeneous impacts of green industrial park policies given resource endowments on carbon emissions and carbon productivity. The results are presented in Table 6.2.1.

Table 6.2.1 Heterogeneity of Resource-based Cities

	(1)	(2)	(3)	(4)
	LC	LC	LCP	LCP
GIP_RB	-0.479	-0.466	0.405	0.389
	(0.125)	(0.125)	(0.126)	(0.125)
GIP	-0.156	-0.146	0.260	0.232
	(0.0776)	(0.0775)	(0.0779)	(0.0778)
PGDP		0.257		0.392
		(0.115)		(0.115)
UL		0.403		-0.588
		(0.749)		(0.752)
PD		-0.447		0.481
		(0.0936)		(0.0940)
OPEN		-0.446		0.319
		(0.286)		(0.287)
FINA		0.276		-0.0750
		(0.147)		(0.148)
Fixed year	Yes	Yes	Yes	Yes
Fixed city	Yes	Yes	Yes	Yes
_cons	3.199	-1.461	3.689	-1.835
	(0.0546)	(2.434)	(0.0548)	(2.443)
N	3324	3324	3324	3324
R^2	0.233	0.242	0.343	0.351
adj.R^2	0.160	0.169	0.280	0.288

Standard errors in parentheses

$p<0.1, p<0.05, p<0.01$

In Table 6.2.1(1), the regression coefficient of GIP_RB is significantly negative. This indicates that, compared to non-resource-based cities, the green industrial park policy has an impact on carbon emissions in resource-based cities. And it is a negative impact. This finding is consistent with (Zhou et al., 2024) [44]. In Table 6.2.1(3), the regression coefficient of GIP_RB is significantly positive. This indicates that, compared to non-resource-based cities, the green industrial park policy has an impact on carbon productivity in resource-based cities. And it is a positive impact.

The results indicate that after the implementation of policies, resource-based cities have significantly reduced urban emissions while significantly improving carbon productivity. The green industrial park policy has significantly influenced the "quantity reduction and quality improvement" of urban carbon emissions. This may be due to the following reasons:

1. Industrial structure of resource-based cities: Resource-based cities primarily produce high-polluting industries such as steel and coal. After the implementation of green industrial park policies, these industries are forced to undergo technological transformation and upgrading, thereby reducing emissions.

2. Path dependence effect of policies: Due to historical development reasons, resource-based cities have a relatively single industrial structure and rely heavily on resource-intensive industries. After the implementation of policies, these cities need to rely more on technological progress and innovation to achieve emission reduction targets.

3. Impact of capital flow: Financial resources are increasingly flowing to resource-based industries. After the implementation of policies, these industries need to make greater technological investments to improve production efficiency and environmental quality, thereby achieving an increase in carbon productivity.

6.2.2. Locational heterogeneity

Cities exhibit significant differences in geographical location, economic scale, environmental awareness, and policy implementation, which may lead to varying responses to green industrial park policies across different cities. We categorize Chinese cities into two parts: the eastern and western regions. The eastern cities are densely populated areas in China, while the northwestern cities are sparsely populated regions.

The eastern cities primarily encompass Beijing, Shanghai, Guangdong, Jiangsu, Zhejiang, and others. These regions boast diverse terrains, including vast plains, hills, and basins. With a suitable climate, abundant precipitation, numerous rivers, and fertile soil, they are ideal for agricultural development. Furthermore, these areas are economically developed, serving as China's economic hub and major industrial, financial, commercial, and technological innovation zones. Most significant special economic zones and coastal open cities are located in this region, which boasts a large economic aggregate, high per capita income, and well-developed infrastructure. Consequently, environmental awareness is relatively strong. However, environmental issues brought about by economic development, such as air pollution and water pollution, are also prominent, garnering significant attention from the public and the government. Many cities have begun implementing strict environmental policies and measures, such as promoting new energy vehicles, constructing green cities, and strengthening pollution control.

The western cities mainly include Xinjiang, Xizang, Gansu, Inner Mongolia, Qinghai, and other cities. These cities have complex terrains, including plateaus, deserts, gobi, and mountains. The climate is relatively arid with low precipitation, and the natural resources are abundant but difficult to develop. Moreover, these cities are relatively underdeveloped, mainly relying on agriculture and mining, with low levels of industrialization and urbanization. The transportation is inconvenient, the infrastructure is weak, and the level of economic development is low. Therefore, the awareness of environmental protection is relatively weak, mainly due to the low level of economic development, and environmental issues are not as urgent as those in the east. However, with the gradual development of the economy and the exploitation of resources, environmental problems have begun to emerge, and environmental awareness is gradually increasing.

Therefore, we set a dummy variable (EW) based on the region where the city is located. If city i is located in the eastern region, then EW=1; otherwise, EW=0. We also constructed a DDD model to test the impact of green industrial parks on the "quality" and "quantity" of urban carbon emissions based on regional differences. The results are shown in Table 6.2.2.

We first examine the reasons behind the impact of the implementation of green industrial park policies on carbon emissions in eastern cities, which exhibit regional heterogeneity. We introduce the GIP_EW variable. The results presented in columns (1) and (2) of Table 6.2.2 indicate that the regression coefficient of GIP_EW is significantly negative in all models, suggesting a notable reduction in emissions in eastern cities following the implementation of GIP policies. This negative regression coefficient for GIP_EW implies that, compared to western cities, the green industrial park policy has reduced carbon emissions in eastern cities, a finding consistent with that reported by Zhang Hua (2020)

Afterwards, we examined the reasons for the impact of green industrial park policies on carbon productivity in cities with regional heterogeneity. The results in columns 6.2.2(3) and (4) show that the regression coefficient of GIP_EW is significantly positive, indicating that carbon productivity in eastern cities has significantly increased after the implementation of GIP policies. This suggests that, compared to western cities, the green industrial park policy has a positive impact on the improvement of carbon productivity in eastern cities. This finding is consistent with (Zhou et al., 2024). The possible reasons are:

High level of economic development: Eastern cities have a higher level of economic development, with a higher degree of industrialization and urbanization, which means that these cities have stronger financial and technological capabilities to implement and promote green industrial park policies. Economically developed cities can more easily invest in clean technology and green infrastructure, thereby reducing carbon emissions. Infrastructure and technological advantages: Eastern cities have relatively well-developed infrastructure and advanced technology, which can enable more effective implementation of green industrial park policies. These cities can utilize advanced technological means to upgrade industrial production, improve energy efficiency, and reduce carbon emissions. Improvement in resource utilization efficiency: Eastern cities have relatively better resource endowments. After implementing green industrial park policies, these cities can utilize resources more efficiently, reduce resource waste, and improve resource utilization efficiency, thereby enhancing carbon productivity.

Technological innovation and industrial upgrading: The implementation of green industrial park policies has driven technological innovation and industrial upgrading in eastern cities. With policy support, these cities have introduced and developed more green technologies and processes, enhancing the environmental protection level and efficiency of the production process, thereby improving carbon productivity.

Table 6.2.2: Regression results of location heterogeneity

	(1)	(2)	(3)	(4)
	LC	LC	LCP	LCP
GIP_EW	-0.368	-0.344	0.337	0.370
	(0.117)	(0.117)	(0.117)	(0.117)
GIP	-0.151	-0.145	0.246	0.200
	(0.0826)	(0.0826)	(0.0829)	(0.0828)
PGDP		0.222		0.438
		(0.116)		(0.116)
UL		0.290		-0.472
		(0.750)		(0.753)
PD		-0.449		0.477
		(0.0938)		(0.0941)
OPEN		-0.460		0.336
		(0.286)		(0.287)
FINA		0.317		-0.0845
		(0.149)		(0.150)
Fixed year	Yes	Yes	Yes	Yes
Fixed city	Yes	Yes	Yes	Yes
_cons	3.094	-1.635	3.851	-1.908
	(0.297)	(2.443)	(0.298)	(2.449)
N	3324	3324	3324	3324
R^2	0.232	0.241	0.343	0.352
adj.R^2	0.159	0.167	0.280	0.288

Standard errors in parentheses

$p<0.1, p<0.05, p<0.01$

6.3. Mechanism regression results

To further verify the transmission mechanism of how green industrial park policies affect carbon emissions and carbon productivity, this paper selects energy utilization efficiency, innovation effect, and structural effect to conduct an impact mechanism test, combining the theoretical analysis above and the viewpoint of (Jiang, 2022)

6.3.1. Energy efficiency

The regression results of the impact of Green Industrial Parks (GIP) on energy efficiency are presented in Table 6.3. The coefficient of the dummy variable for Green Industrial Parks (GIP) in column (1) of Figure 6.3 is 0.002 and is significant at the 1% significance level (P<0.000). Green Industrial Parks typically introduce and promote clean energy technologies, such as solar and wind energy. The application of these technologies can significantly reduce dependence on fossil fuels and improve energy utilization efficiency. At the same time, buildings and infrastructure within Green Industrial Parks often adopt energy-saving designs and materials, such as high-efficiency insulation materials and energy-saving lighting systems. These green buildings and infrastructure can significantly reduce energy consumption and improve energy utilization efficiency. As an important indicator reflecting the internal structure of energy consumption, energy utilization efficiency is a crucial means for achieving carbon emission reduction, especially when implementing proactive energy efficiency measures is the most effective way to reduce emissions. Therefore, Green Industrial Park policies can accelerate the transformation of the internal structure of energy consumption, improve energy utilization efficiency, and effectively curb total carbon emissions and promote carbon productivity. Hypothesis 2 is verified

6.3.2. Innovation effect

The regression results of the green industrial park policy on urban innovation level are listed in (2) of Table 6.3. Green Industrial Park (GIP): the coefficient is 51.27, which is significant at the 1% significance level ($P<0.000$), indicating that the implementation of the green industrial park policy has improved the city's innovation capability. This result is similar to that of Zhou et al. Green industrial parks promote urban innovation level through technology and knowledge agglomeration effects: typically, they gather a group of high-tech enterprises and research institutions. This agglomeration effect facilitates the sharing and dissemination of technology and knowledge, promoting the occurrence of innovation activities. Interaction and cooperation among enterprises can stimulate new innovative ideas and technological breakthroughs. At the same time, green industrial parks often attract a large number of high-quality talents and focus on talent cultivation and training. These talents are important driving forces for innovation activities, and their knowledge and skills provide strong support for enterprise innovation. Urban innovation capability plays an important role in carbon emission reduction by accelerating the low-carbon transformation of industrial equipment and the research and development of renewable energy and bio-carbon sequestration technologies, thereby reducing carbon emissions from the root. Thanks to the technological progress effect brought by urban innovation, it helps stimulate regional innovation vitality and sustained economic growth, thereby improving carbon productivity. Hypothesis 3 is verified

6.3.3. Industrial agglomeration

The regression results of the impact of green industrial parks on the degree of industrial agglomeration are listed in (3) of Table 6.3. It can be observed that the impact coefficient on industrial agglomeration is 0.0133, and its p-value is 0.0037, which is less than 0.01, indicating that this impact is statistically significant. Hypothesis four is verified.

Table 6.3: Test of GIP on Carbon Emission Mechanism

	(1)	(2)	(3)
	EE	INNO	AGG
GIP	0.00220	50.37	0.0133
	(0.000334)	(4.799)	(0.00674)
PGDP	0.00715	-4.928	0.255
	(0.000562)	(8.075)	(0.0113)
PD	0.00109	33.75	-0.00480
	(0.000458)	(6.572)	(0.00923)
UL	-0.0394	-923.4	0.120
	(0.00366)	(52.58)	(0.0739)
OPEN	-0.000505	25.22	0.118
	(0.00140)	(20.04)	(0.0282)
FINA	0.000709	-4.250	-0.0310
	(0.000720)	(10.33)	(0.0145)
Fixed year	Yes	Yes	Yes
Fixed city	Yes	Yes	Yes
_cons	-0.0781	-54.91	-1.066
	(0.0119)	(170.8)	(0.240)
N	3324	3324	3324
R^2	0.418	0.192	0.162
adj.R^2	0.362	0.113	0.081

Standard errors in parentheses

$p<0.1, p<0.05, p<0.01$

6.3.4. Analysis of the mechanism of resource endowment heterogeneity

This article further explores the reasons behind the dual impact of resource endowment heterogeneity on the implementation of green industrial park policies and urban carbon emission reduction. We introduce the GIP_RB variable into the model and analyze it using the DDD model. The results in Table 6.3.4 show that the regression coefficients of GIP are all significantly positive, while the regression coefficient of GIP_RB in column (1) is significantly negative, indicating that for resource-based cities, green industrial park policies reduce the energy efficiency of resource-based cities, thereby diminishing the impact of green industrial parks on urban carbon emissions

The results in column (2) indicate that the innovation effect of resource-based cities is negative compared to non-resource-based cities. The possible reasons are as follows: Firstly, the monopoly characteristics of resource-based cities, which are dominated by steel and coal, make it difficult for the market's "survival of the fittest" mechanism to function. This results in a weaker competitive effect. Secondly, resource-based cities, especially those with high resource dependence, are more prone to path dependence in their development process. Resource-based industries are mostly pollution-intensive and have low levels of production technology. Implementing green industrial park policies to encourage enterprises to save energy and reduce emissions greatly increases their costs. Thirdly, the profit-driven nature of capital further drives financial resources towards resource-based industries, which has a negative impact on production efficiency and environmental quality. Therefore, the implementation of green industrial park policies hinders technological progress and innovation in resource-based cities.

The regression results in column (3) indicate that the green industrial park policy in resource-based cities has enhanced the degree of urban industrial agglomeration. Through economies of scale and technological effects, it can help optimize resource allocation, accelerate technology diffusion and dissemination, stimulate technological innovation of enterprises, improve energy utilization efficiency and production efficiency, thereby reducing urban carbon emissions and enhancing carbon productivity in green industrial parks in resource-based cities (Lin and Zhu, 2020)[21].

Table 6.3.4: Analysis of Carbon Emission Mechanism in Resource-based Cities

	(1)	(2)	(3)
	EE	INNO	AGG
GIP_RB	-0.00470	-85.86	0.0364
	(0.000603)	(8.612)	(0.0123)
GIP	0.00357	75.50	0.00269
	(0.000375)	(5.354)	(0.00763)
PGDP	0.00722	-3.652	0.255
	(0.000557)	(7.948)	(0.0113)
PD	0.00115	34.72	-0.00521
	(0.000453)	(6.469)	(0.00922)
UL	-0.0392	-918.7	0.118
	(0.00363)	(51.75)	(0.0738)
OPEN	-0.000418	26.81	0.117
	(0.00138)	(19.73)	(0.0281)
FINA	0.000562	-6.938	-0.0298
	(0.000713)	(10.17)	(0.0145)
Fixed year	Yes	Yes	Yes
Fixed city	Yes	Yes	Yes
_cons	-0.0767	-28.71	-1.077
	(0.0118)	(168.1)	(0.240)
N	3324	3324	3324
R^2	0.430	0.217	0.164
adj.R^2	0.374	0.141	0.083

Standard errors in parentheses

p<0.1,p<0.05,p<0.01

6.3.5. Analysis of the mechanism of location heterogeneity

We further explored the reasons for the location heterogeneity of the impact of green industrial park (GIP) policy implementation on urban carbon emissions. We introduced the GIP_EW variable into the model and analyzed it using the DDD model. The results are presented in Table 5.3.5, indicating that the regression coefficients of GIP are all significantly positive. The regression coefficients of GIP_EW in columns (1), (2), and (3) are significantly positive, suggesting that compared to the western region, the implementation of the green industrial park policy has promoted the development of EE, INNO, and AGG in the eastern region.

The implementation of green industrial park policies has significantly improved energy efficiency, innovation effects, and industrial agglomeration. Enterprises require substantial financial and human capital support for technological research and development and innovation. Compared to the western region, the eastern region boasts abundant human capital and more investment. The eastern region mainly features a higher level of market-oriented factor allocation. The implementation of green industrial park policies has further promoted the green development of industrial parks in the eastern region.

Table 6.3.5 Analysis of Carbon Emission Mechanism in Eastern Cities

	(1)	(2)	(3)
	EE	INNO	AGG
GIP_EW	0.00354	108.2	0.0617
	(0.000566)	(7.939)	(0.0114)
GIP	0.000798	7.412	-0.0108
	(0.000401)	(5.624)	(0.00808)
PGDP	0.00754	4.652	0.264
	(0.000563)	(7.896)	(0.0114)
PD	0.00101	32.43	-0.00714
	(0.000455)	(6.388)	(0.00918)
UL	-0.0385	-895.8	0.136
	(0.00364)	(51.09)	(0.0734)
OPEN	-0.000410	27.27	0.120
	(0.00139)	(19.46)	(0.0280)
FINA	0.000751	-9.847	-0.0249
	(0.000725)	(10.18)	(0.0146)
Fixed year	Yes	Yes	Yes
Fixed city	Yes	Yes	Yes
_cons	-0.0801	-64.59	-1.139
	(0.0119)	(166.3)	(0.239)
N	3324	3324	3324
R^2	0.426	0.238	0.173
adj.R^2	0.370	0.164	0.093

Standard errors in parentheses

$p<0.1$,$p<0.05$,$p<0.01$

7. Conclusion

This study validates the effectiveness of green industrial park policies in promoting carbon reduction and improving carbon productivity, indicating that policy implementation can effectively alleviate the carbon emission pressure brought by traditional industrial parks. Specifically, the policy of green industrial parks has achieved a "quantity reduction and quality improvement" of carbon emissions by promoting green technology innovation, optimizing energy structure, and enhancing industrial agglomeration level. The research results show that cities implementing policies not only significantly reduce carbon emissions, but also significantly improve carbon productivity, reflecting the dual benefits of policies on the economy and environment.

In addition, the study revealed differences in policy responses between resource-based cities and eastern cities. The carbon emissions of resource-based cities have significantly decreased, while carbon productivity has also improved, indicating that the policy of green industrial parks has effectively promoted the industrial transformation and technological upgrading of these cities. Eastern cities, due to their higher level of economic development, are more likely to attract technology and investment, thus achieving faster technological innovation and improved resource utilization efficiency after implementing green industrial park policies.

It is worth mentioning that this article successfully solved the endogeneity problem and enhanced the reliability of empirical results by using railway opening data from the Republic of China as instrumental variables. This innovation provides new ideas for subsequent research, suggesting that researchers should consider the severity of endogeneity issues when dealing with similar economic policy impacts and seek appropriate instrumental variables for effective testing.

In the future, policy implementation should pay more attention to regional characteristics in order to develop more effective green development strategies targeted at cities at different stages of economic development. Especially in resource-based cities, it is necessary to strengthen technical support and capital investment to promote the green transformation of industrial structure. Meanwhile, eastern cities should continue to leverage their technological and financial advantages, and further promote sustainable economic development by deepening policies for green industrial parks. Policy makers should also strengthen the coordinated development between regions, promote the sharing of technology and experience, in order to achieve a comprehensive low-carbon economic transformation and ensure the smooth achievement of the country's "dual carbon" goals.

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