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The Impact of Industrial Agglomeration on Urban Carbon Emissions: An Empirical Study Based on the Panel Data of China's Prefecture-Level Cities

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Abstract: In the context of accelerating global climate change, it has become increasingly important to study the vital relationship between industrial agglomeration and urban carbon emissions for sustainable development. The present study focuses on the influence of industrial agglomeration on urban carbon emissions, by investigating a sample of 280 prefecture-level cities in China from 2009 to 2021. Methodologically, this study empirically tests the effect of industrial agglomeration on the urban carbon emissions through the use of a spatial Durbin model and mediating effect model. The following are the main conclusions: first, the impact of industrial agglomeration on urban carbon emissions shows an inverted U-shaped relationship, which first intensifies and then inhibits, and has spatial spillover effect; second, industrial agglomeration has different impacts on urban carbon emissions in the eastern, central and western regions. Industrial agglomeration shows different impacts on urban carbon emissions between resource-based and non-resource-based cities. Industrial agglomeration shows different impacts on urban carbon emissions between old industrial cities and non-old industrial cities. Third, green technology innovation and green talent agglomeration mediate the relationship between industrial agglomeration and urban carbon emissions. This study highlights the significance of industrial agglomeration in promoting sustainable urban development and offers valuable insights for the planning and formulation of industrial development policies.

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Keywords: industrial agglomeration; urban carbon emissions; green technology innovation; green talent agglomeration

1. Introduction

On the issue of global warming, the overwhelming majority of countries have reached the consensus that the increase in carbon dioxide concentration is the main cause of global climate fluctuation [1]. By the U.S. Carbon Dioxide Information Center (CDIAC), global carbon emissions skyrocketed from 3 million tons of carbon in 1751 to 9.855 billion tons in 2014. As the world's top carbon emitter, China has taken up 80% of the increase in carbon dioxide since 2008 [2]. Recognizing the grave challenges of global climate change, many countries have joined hands to strengthen the awareness of sustainable development. On 22 September 2020, during the general debate of the United Nations General Assembly's 75th session, China committed itself to peaking its carbon emissions by 2030 and reaching carbon neutrality before 2060. However, the problem of reducing carbon emissions is inseparable from China's national industrial development [3]. Currently, China's economy has embarked on a new stage of robust developments. Traditional production models are facing severe challenges, while economic growth needs to focus on improving economic quality. Obviously, substantive economic progress cannot be separated from high-quality industrial agglomeration [4], and industrial agglomeration as a spatial type of interaction between production factors has higher organizational efficiency

[5]. However, pollution emission patterns resulting from the early agglomeration have caused serious ecological problems [6]. Within the background of the “Dual Carbon” target, environmental issues and industrial development should be carefully considered and coordinated [7]. Therefore, studying whether the spillover effects of industrial agglomeration are environmentally favorable or unfavorable has important theoretical and practical implications for promoting sustainable development. However, the current studies on the relationship and causal mechanism between industrial agglomeration and urban carbon emissions remain insufficient.

As such, this research aims to examine the impacts of industrial agglomeration and urban carbon emissions. Furthermore, this study seeks to clarify the transmission mechanism in the course of industrial agglomeration affecting carbon emissions in Chinese cities. To start with, this research selects the data of China’s 280 prefecture-level cities from 2009 to 2021 to calculate their industrial agglomeration level and carbon emissions over the years. The temporal and spatial agglomeration trends of the two are then analyzed. Second, in accordance with the spatial Durbin model, this study draws on the data of China’s National Bureau of Statistics, examines the impacts of industrial agglomeration on urban carbon emissions and spatial spillover impacts, and carries out heterogeneity analysis. Finally, this research combines the mediating effect model with the spatial Durbin model to illustrate the influencing mechanism of industrial agglomeration on urban carbon emissions.

The contributions of this study are threefold: first, it focuses on the effects of industrial advances on urban sustainability from a standpoint of industrial agglomeration, thus expanding the research scope of industrial economics. Second, previous studies have mostly centered on the causal factors of carbon emissions in light of China’s provincial-level data, while this study looks into the link between industrial agglomeration and carbon emissions with more substantive data from China’s prefecture-level cities, while testing the impacts of their divergent results in light of the different developmental characteristics of various cities. Third, on the influences wrought by the process of industrial agglomeration, few scholars have integrated the green technology innovation and green talent agglomeration effect into the conceptual framework for analysis as a mechanism variable. This study incorporates green technology innovation and green talent agglomeration into the research model, and targets at analyzing the internal mechanism between industrial agglomeration and urban carbon emissions. A further understanding into the causal factors of regional carbon emissions and their mechanisms can provide solid scientific foundation of policy-making for economy-cum-environment sustainability in China’s development.

The remainder of this article is structured as follows: Section 2 provides the literature review. Section 3 explains the theoretical framework and proposes the research hypotheses. Section 4 introduces the materials and methods. Section 5 summarizes and interprets the statistical findings and analytical implications. Last, Section 6 concludes the research and expands on its meanings.

2. Literature Review

2.1. Industrial Agglomeration

In terms of environmental externalities of industrial agglomeration, there are three prevalent views on this topic: first, the environmental degradation theory argues that industrial agglomeration drives up economic scale, but the resultant expansion of production capacity, together with the relaxing environmental regulations by local governments, inevitably brings about pollution emissions. Grounded on the panel data of European cities, Leeuw et al. confirmed that industrial agglomeration results in the increase in air pollution emissions [8]. Zhao et al. reviewed the panel data of China’s resource-based cities and concluded that industrial agglomeration will cause environmental pollution [9]. Second, the environmental improvement theory emphasizes that industrial agglomeration

could lower pollution emissions, through reducing environmental governance expenses [10] and enhancing technology spillovers [11]. Third, different from the above two linear views, the nonlinear relationship theory holds that industrial agglomeration has a complex nonlinear relationship with environmental pollution. Ye et al. took the data of China's prefecture-level cities as samples and discovered that the relationship between haze pollution in the central and eastern areas caused by industrial agglomeration presented a typical inverted U-shaped trajectory [12]. Chen et al. further employed the spatial econometric model to explore the link between industrial agglomeration and spatial pollution and found that industrial agglomeration shows an inverted U-shaped effect on urban air pollution via the knowledge spillover effect, and this effect has a spatial spillover impact. [13]. Zhao et al. applied the same spatial measurement model, treating technological innovation as the mechanism variable. They discussed the relationship between industrial agglomeration and spatial pollution and found that industrial agglomeration demonstrates an inverted U-shaped effect on urban haze, while this effect also has a spatial spillover result [14]. In line with the spatial dynamic panel model and treating technological innovation as the mediating variable, some scholars posit an N-shaped relationship between industrial agglomeration and environmental pollution [15].

While reviewing the above literature, the present study finds that, though the current research on the environmental externalities of industrial agglomeration is quite expansive, their observations and judgements are quite divergent, which seems to be most controversial. This study suggests that there can be more than one linear tie between industrial agglomeration and environmental pollution. At the same time, if the panel data are used and the spatial spillover effect is ignored, the result will be unreliable.

2.2. Carbon Emissions

There have been abundant studies on carbon emissions. The relevant literature mainly centers on the measurement of carbon emissions and the influencing factors of carbon emissions. In terms of carbon emission measurement methods, index decomposition analysis method [16], structural decomposition analysis method [17], IPCC method [18] and so on are mainly applied in nature. The metric objects of carbon emissions mostly concentrate on the national level [19], provincial level [18] and municipal level [20].

The studies on the impacting factors of carbon emissions are mostly divided into macro perspective and micro perspective. From the macro perspective, classical studies on the factors affecting carbon emissions primarily focus on the effects of environmental regulation [21] and economic growth [22]. From the micro perspective, most research focuses on the factors affecting corporate carbon emissions. Doda et al. studied the effects of corporate carbon management on corporate carbon emissions for the first time [23]. Konadu et al. investigated the impacts of gender divergences in the board of directors on corporate carbon emission reduction [24]. Li et al. discussed in depth the mechanism of ESG rating in reducing corporate carbon emissions [25]. To sum up, scholars have obtained fruitful results on carbon emission measurements and influencing factors from different perspectives.

2.3. Industrial Agglomeration and Carbon Emissions

There have been various studies on the link between industrial agglomeration and carbon emissions. Yet, there is no uniform conclusion on the direction of industrial agglomeration's effects on carbon emissions. Some scholars believe that industrial agglomeration will only aggravate carbon emissions [26,27], while other scholars hold the opposite view, suggesting that appropriate industrial agglomeration can reduce regional carbon emissions [28,29]. Nevertheless, most scholars agree on a nonlinear relationship between industrial agglomeration and carbon emissions. Li et al. based their study on provincial panel data and applied the dynamic panel model to reveal the inverse U-shaped tie between industrial agglomeration and carbon emission intensity. They point out that technological progress acts as the intermediary mechanism of industrial agglomeration

impacting carbon emission intensity [30]. Tian et al. believe that the clustering of manufacturing and service industries demonstrates a U-shaped impacting trajectory on carbon emission efficiency by propelling urban green progress, accompanied by the spatial spillover effect and geographical location diversity [31].

Clearly, current studies have not led to a consensus on the impacts of industrial agglomeration on carbon emissions, and the impact mechanism of carbon emissions remains to be clarified. Specifically, most studies take provinces as the target samples, which ignore the differences between prefecture-level cities within said provinces. This also neglects regional heterogeneity in the relationship between industrial agglomeration and carbon emissions. To address this significant deficiency, this study selects 280 prefecture-level cities in China as the sample and conducts heterogeneity analysis according to those cities' geographical and development differences. In addition, most scholars take conventional technological innovation as the transmissive mechanism between the two. However, not all technological innovations can play a role in pollution control. Compared with conventional technology innovation, green technology innovation with preference orientation has more externalities of environmental governance and knowledge spillover. Therefore, this study takes green technology innovation and green talent agglomeration as the mediating variables to more accurately reveal the transmissive path of industrial agglomeration on urban carbon emissions. As such, this study enlarges the current understanding and knowledge on this topic and improves the quality and efficiency of the policy-making process in support of sustainable development.

3. Theoretical Analysis

3.1. Influence of Industrial Agglomeration on Urban Carbon Emissions

In the field of economics, the Kuznets theory, introduced by Simon Kuznets during the 1950s, aimed to illustrate the dynamic interplay between income inequality and economic growth. Subsequently, Grossman et al. adapted this concept to environmental science, formulating the environmental Kuznets curve [32]. This curve suggests that environmental pollution tends to escalate in the initial phases of economic development but begins to decline after surpassing a critical threshold, thereby exhibiting an inverted U-shaped trajectory. Similarly, the relationship between industrial agglomeration and urban carbon emissions might also display a nonlinear pattern, where the inverted U-shape is primarily influenced by the specific characteristics associated with varying levels of agglomeration. [33]. At the early stage of industrial agglomeration, on the one hand, the scale of the cluster gradually expands and leads to an increase in the total production capacity, which makes the urban carbon emissions increase significantly [34]. On the other hand, according to the pollution haven hypothesis (PHH) [35], at the early stage of industrial agglomeration, manufacturers pay more attention to the changes on the demand side, while the access standard of enterprises in the agglomeration area remains low [27]. Hence, most regions tend to rely on the improvement in supply quantity to achieve industrial development, while ignoring the quality of supply. This results in the lack of implementation of environmental protection in the operation and management of most enterprises, culminating in various problems due to a high proportion of backward production capacity [36].

With significant advancements in the level of industrial agglomeration, stricter supervision of pollution concentrations has been implemented [37], effectively mitigating environmental risks associated with pollutant emissions and enabling regions to achieve benefits in energy conservation and emission reductions. Simultaneously, the enhancement of industrial agglomeration facilitates a more rapid circulation of production factors, promotes their optimal allocation and enhances efficiency in the division of labor and collaborative processes [38]. The coopetition relationship of various agglomeration subjects drives knowledge spillover and innovation competition, while promoting the green mode of production [39,40]. For instance, the improvement in industrial agglomeration level has

gradually changed China's path of dependence on traditional production, thus helping it achieve the goal of sustainable development [41]. In short, driven by multiple agglomeration subjects, high-level industrial agglomeration can inhibit the increase in urban carbon emissions.

Additionally, industrial agglomeration influences regional carbon emissions and transcends geographical boundaries, leading to spatial spillover effects on adjacent areas. In the initial phases of expansion, industrial agglomeration can result in overlapping carbon emissions across regions, transferring outdated and surplus capacity to neighboring areas, which in turn leads to a concentration of carbon emissions in those areas. [30]. With the improvement in industrial agglomeration level, it will trigger the "demonstration-cum-imitation" effect in the surrounding areas, improve the original over-production mode of the surrounding cities, introduce a large number of green and clean technologies and achieve the continuous emission reduction [42]. Moreover, the improvement in industrial agglomeration level can also promote the sharing of high-quality production factors, form the factor base of low-carbon production, and achieve the goal of sustainable urban development.

Based on the above theoretical review and conceptual foundation, this study puts forward Hypothesis 1:

Hypothesis 1. *Industrial agglomeration has an inverted U-shaped relationship with spatial spillover effect on urban carbon emissions.*

3.2. Analysis of the Influencing Mechanism of Industrial Agglomeration on Urban Carbon Emissions

Technological innovation plays an increasingly crucial role in the optimization of industrial structure. The heterogeneity of technological innovation preferences brought about by industrial development changes the impact path of production technology on the environment. When scientific research and innovation adhere to green orientation, it will inhibit the damage of production and business activities to environmental quality [43]. First, according to Marshall's *Principles of Economics* and Perroux's growth pole theory on technological externalities of industrial agglomeration, industrial agglomeration can promote the diffusion of technology in the agglomeration area [38], realize the interdisciplinary integration of technologies in different fields and improve the capacity to acquire key green technology information, thus promoting the output of green technology innovation [44]. This process provides technical support for urban sustainable development. Second, Weber, in his theory of industrial location, argued that industrial agglomeration can reduce costs. After the improvement in industrial agglomeration level, production costs can be saved through sharing infrastructure and other means, which can in turn drive enterprises' green technology innovation, induce enterprises' "innovation compensation" and enhance enterprises' low-carbon production and continuous emission reduction [45]. Third, according to Porter's competitive advantage theory, the competition effect and learning effect formed by industrial agglomeration can effectively enhance regional innovation ability and build regional competitive advantage [46]. Specifically, high-tech industries with higher requirements for new energy technology, green products and green innovation resources have a more intense competitive ecology within their agglomeration areas. In addition, with the increase in similar enterprises in the cluster area, the limited space, market share and resources and the elevation of the industry entry threshold will also increase the competitive pressure of these high-tech enterprises [47]. Therefore, enterprises in the agglomeration area will continue to carry out green innovation to obtain competitive advantages, and this competition and demonstration effect will also promote other agglomeration areas in the adjacent region to adopt green innovation strategies to improve their green innovation efficiency [48]. Then, in the mature stage of industrial agglomeration, carbon emissions of cities and surrounding areas can be reduced.

Based on the above analysis, this study puts forward Hypothesis 2:

Hypothesis 2. *Industrial agglomeration can affect urban carbon emissions through green technology innovation.*

Industrial agglomeration reduces the cost of information search, creates a favorable innovative atmosphere for the region and attracts talents from related industries [49]. First of all, the new economic geography theory represented by Krugman's "center-periphery" model holds that the cross-regional flow of human resources will make the centripetal force of resource concentration dominate in a certain region and form a central region dominated by the concentration of high-quality human resources [50]. The characteristics of the production network of industrial clusters can generate the accumulation of information factors, form a reservoir of highly skilled labor and provide environmental protection and professional personnel support for enterprises' sustainable development [51]. Second, Jacob's externality theory also highlights the effect of industrial agglomeration on cross-industry and intra-industry knowledge spillover [45]. Industrial agglomeration promotes the exchange of environmental protection technicians between heavy polluting enterprises and non-heavy polluting enterprises [52]. Environmental protection knowledge spillover between upstream and downstream enterprises can promote the low-carbon transformation of the industry. Finally, according to sustainable development theory, the effect of green talent accumulation brought about by industrial agglomeration can also improve the cultural and environmental literacy of residents in and around the cities where the agglomeration area is located [53]. The promotion of environmental protection concepts has made the public inclined to develop green living habits and cooperate to reduce urban carbon emissions.

Based on the above analysis, this study puts forward Hypothesis 3:

Hypothesis 3. *Industrial agglomeration can affect urban carbon emissions through green talent agglomeration.*

Consistent with the proposed hypothesis, Figure 1 illustrates the conceptual model framework of this study.

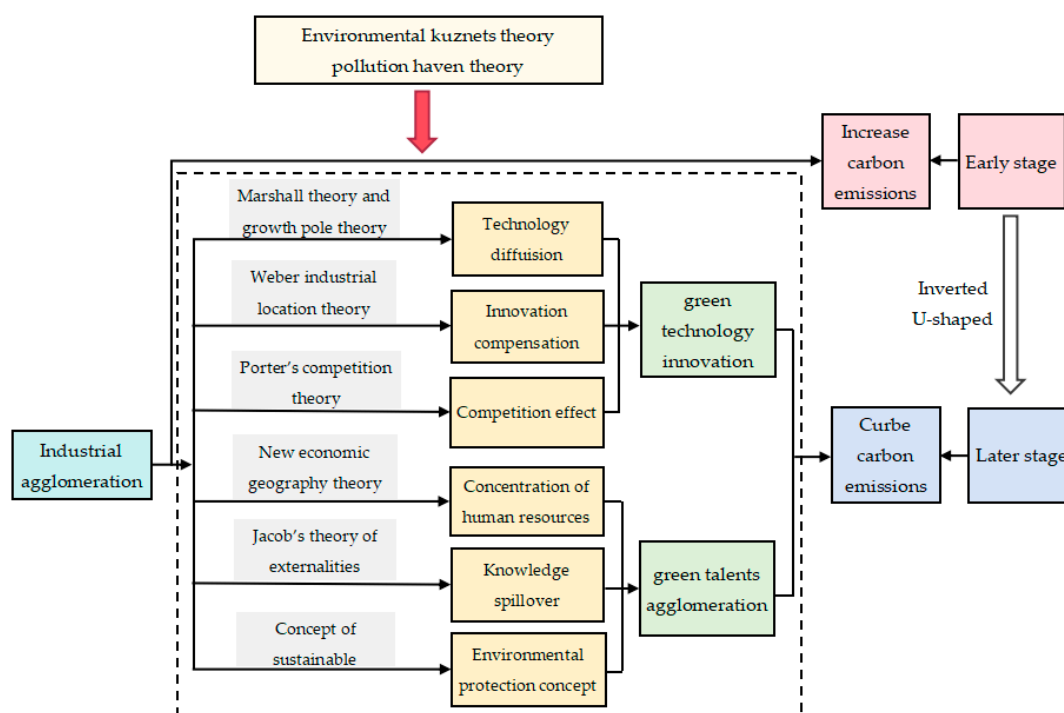


Figure 1. The conceptual model diagram of this research.

4. Materials and Methods

4.1. Variable Selection and Data Sources

4.1.1. Dependent Variable

In this study, urban carbon emissions (CO_2) are used as the explained variable and calculated by the IPCC method. According to the calculation method of Kena Mi et al. [29], when calculating the carbon emissions of each prefecture-level city, this study selects the consumption of 17 kinds of energy such as crude oil, liquefied petroleum gas and gasoline to calculate the carbon emissions of each city. The specific formula is as follows:

$$\text{CO}_2 = \sum_{i=1}^{17} B_i \times C_i \quad (1)$$

Among them, CO_2 is carbon emissions. B_i is the consumption of the i th energy. C_i is the carbon emission coefficient of the i th energy. i is the number of energy types.

4.1.2. Independent Variable

Referring to the practice of Zhang et al. [26], this study uses the location entropy method to measure the industrial agglomeration level (Agg) of each city, and its calculation formula is as follows:

$$\text{Agg}_{ij} = \frac{\frac{E_{ij}}{\sum_{i=1}^n E_{ij}}}{\sum_{j=1}^n \frac{E_{ij}}{\sum_i \sum_j E_{ij}}} \quad (2)$$

where E_{ij} represents the output value of industry i in region j ; $\sum_{i=1}^n E_{ij}$ represents the total output value of region j ; $\sum_{j=1}^n E_{ij}$ represents the total output value of industry i ; $\sum_i \sum_j E_{ij}$ represents the total national output value.

4.1.3. Mediating Variable

Green technology innovation (GTI). In the aspect of green technology innovation, most traditional studies take patents as the simple index. While the number of patents is valuable, it may not multidimensionally reflect the overall level of green technology innovation in cities. In order to provide a more comprehensive view of green technology innovation, thus capturing both the number of innovations and their actual environmental benefits, this study refers to the practice of Liu et al. [54], and adopts the super-efficiency SBM model. By adding unwanted outputs to the model, the problem of slack and rank juxtaposition of input and output can be effectively solved.

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

$$\text{s.t.} \begin{cases} \bar{x} \geq \sum_{j=1, \neq k}^n x_{ij} \lambda_j; \bar{y}^d \leq \sum_{j=1, \neq k}^n y_{sj}^d \lambda_j; \bar{y}^d \geq \sum_{j=1, \neq k}^n y_{qj}^d \lambda_j; \\ \bar{x} \geq x_k; \bar{y}_k^d \leq y_k^d; \bar{y}^u \geq y_k^u; \\ \lambda_j \geq 0, i = 1, 2, \dots, n, j \neq 0; \\ s = 1, 2, \dots, r_1; q = 1, 2, \dots, r_2; \end{cases} \quad (3)$$

In Formula (3), it is assumed that there are n DMUs, and each DMU is composed of input m , expected output and undesired output. x , y^d , y^u are the elements in the corresponding input matrix, expected output matrix and undesired output matrix. r^* is urban GTI.

This study initially examines three categories of innovation input factors crucial for urban green innovation activities. These consist of: (1) Capital input, assessed by urban science and technology expenditures (ten thousand yuan), indicating the level of local government support for scientific and technological innovation [55]. (2) Labor input, evaluated by the workforce involved in water, urban environment and public services (ten thousand individuals) [56]. (3) Energy input, measured by total industrial energy consumption (tons) [57]. Subsequently, this study identifies six output variables, comprising three expected and three unexpected outcomes. Among the expected outputs, economic output is gauged by the sales revenue of new green products (ten thousand yuan), which signifies the degree of commercialization of green innovation achievements. Technological output, determined by the number of green patents granted (in pieces), refers to the classification in the Green List of International Patent Classifications' issued by WIPO in 2010. Ecological output is quantified by the green coverage rate of built-up areas (%), as per existing studies [58]. For unexpected outputs, metrics include emissions of industrial sulfur dioxide (tons), industrial wastewater (tons) and industrial solid waste (tons).

Green talents agglomeration (STA). Referring to the way of measuring the agglomeration degree of scientific and technological talents in the existing research [49], the agglomeration degree of green talents is measured and used as the second mediating variable.

$$STA_i = \frac{ST_i / TL_i}{ST / TL} \quad (4)$$

where ST_i represents the number of green talents in city i , and TL_i represents the year-end population of city i ; ST and TL denote the national number of green talents and the national year-end population, respectively. For the selection of indicators of green talents, according to the standard of industry classification of National Economy (GBT 4754-2011), this study selects the number of employees in urban units of research and experimental development, environment and public facilities management, science and technology promotion and application service as the proxy variable of green skilled talents, and performs logarithmic processing.

4.1.4. Controlled Variable

Referring to the existing research, the regional economic development level [27], population [12], fixed asset investment [59], urban electricity consumption [29] and the number of industrial enterprises above the designated size are also the main influencing factors

of urban carbon emissions [60]. The above variables are selected as control variables in this study. Among them, per capita GDP is the ratio of urban GDP to the average population of the region in the current year. The population size is the number of urban population inhabitants at the end of the year. Investment in fixed assets is the measure of annual average net value of urban fixed assets. Urban electricity consumption is the annual electricity consumption of the city. The number of industrial enterprises above the designated size refers to the number of enterprises with a main business income of more than 20 million yuan in the sample cities.

Table 1 shows the measurement methods, units and reference sources of independent variables, dependent variables, mediating variable variables and control variables in detail.

Table 1. Measurement and origin of variables.

Variable	Implication	Measurement Mode	Unit	Reference
CO ₂	Carbon dioxide emissions	IPCC method	Ten thousand tons	[29]
Agg	Industrial agglomeration level	Location entropy method	— —	[26]
pop	Urban population	Urban population at the end of the year	Thousands of people	[12]
rgdp	Per capita GDP	GDP/urban population	Yuan per person	[27]
scal	Investment in fixed assets	Average annual net value of urban fixed assets	Ten thousand yuan	[59]
ele	Urban electricity consumption	The urban's total annual electricity consumption	Ten thousand kilowatt-hours	[29]
enter	Number of industrial enterprises above designated size	The number of enterprises in the city whose main business income exceeds 20 million yuan	Pieces	[60]
GTI	Green technology innovation	Super-efficiency SBM model	— —	[54]
STA	Green talents agglomeration	Location entropy method	— —	[49]

4.1.5. Data Sources

This study selects the panel data of 280 prefecture-level cities in China from 2009 to 2021 (excluding Hong Kong, Macao and Taiwan) as the research sample. The relevant data mainly come from the *China Statistical Yearbook*, *China Statistical Yearbook on Environment*, *China Statistical Yearbook on Cities*, *China Statistical Yearbook on Energy* and *China Statistical Yearbook on Population and Employment* over the years, as well as the statistical yearbooks and statistical bulletins of relevant prefecture-level cities. Missing data were completed by moving average method and linear interpolation method. In addition, considering the unification of data dimensions and the reduction in heteroscedasticity, the logarithm and winsorization of urban carbon emissions and control variables are carried out. Before the empirical analysis, the IPS and LLC methods are used to conduct the unit root test on the panel data. Through further cointegration analysis, all statistics pass the test at the significance level of 5%, and it can be judged that there is a long-term stable equilibrium relationship among the industrial agglomeration level, urban carbon emissions and each control variable. Table 2 displays descriptive statistics for each variable index value in this study.

Table 2. Descriptive statistics of the variables.

Variable	Observations	Mean	Std.Dev.	Min	Max
CO ₂	3640	8.059	0.537	6.391	11.316
Agg	3640	0.518	0.176	0.075	3.898
pop	3640	5.912	0.663	3.400	8.136

rgdp	3640	10.657	0.626	4.595	13.055
scal	3640	16.282	0.985	9.773	19.401
ele	3640	13.143	1.314	6.536	17.034
enter	3640	5.526	1.264	0	9.475
GTI	3640	0.215	0.048	0.005	2.941
STA	3640	0.611	0.487	0.103	3.177

4.2. Spatial Autocorrelation Test

Before studying the spatial effect of industrial agglomeration on carbon emissions, Moran's I should be used to test the spatial autocorrelation of the research objects. Among them, the global Moran's I can reflect the overall spatial autocorrelation of variables, while the local Moran's I measures the agglomeration characteristics of different individuals of variables. The global Moran's I can be calculated as follows:

$$I = \frac{\sum_{i=1}^n \sum_{j=1}^n w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{S^2 \sum_{i=1}^n \sum_{j=1}^n w_{ij}} \quad (5)$$

The local Moran's I can be calculated as follows:

$$I_i = \frac{(x_i - \bar{x})}{S^2} \sum_{j=1}^n w_{ij} (x_j - \bar{x}) \quad (6)$$

In the above two equations, x_i , x_j , $S^2 = \frac{\sum_{i=1}^n (x_i - \bar{x})^2}{n}$ represent the variable value of the i city and the j city and the variance of the variable value. w_{ij} is the element in the spatial weight matrix. Selecting an appropriate spatial weight matrix is the premise and key to accurately evaluate the spatial effect of industrial agglomeration on urban carbon emissions. Since geographically adjacent cities have similar resource endowments, the spillover effect of environmental pollution and low-carbon technology may be more significant. Firstly, the spatial weight matrix of geographical distance (W_1) is established, and the construction formula is as follows:

$$W_1 = (w_{ij})_{n \times n} = \begin{cases} \frac{1}{d_{ij}^2} & i \neq j \\ 0 & i = j \end{cases} \quad (7)$$

In Equation (7), element d_{ij} of W_1 represents the nearest surface distance between the center point of cities i and j . In addition, the industrial structure of cities will exhibit similarities when their economic growth trajectories align. Therefore, the spatial weight matrix of economic distance (W_2) is constructed, and the formula is as follows:

$$W_2 = (w_{ij})_{n \times n} = \begin{cases} \frac{1}{|y_i - y_j|} & i \neq j \\ 0 & i = j \end{cases} \quad (8)$$

In Equation (8), element y_i and y_j represent the annual per capita GDP of i city and j city, respectively. However, considering that the spatial weight matrix of geographical distance (W_1) cannot fully include economic development factors, and the economic distance weight matrix (W_2) is prone to endogenous problems, this study further constructs

and finally uses the geographic economy nested spatial matrix (W_3). In this way, it not only considers the geographical distance between cities, but also incorporates the radiation effect among different economic zones, thereby providing a more comprehensive reflection of the spatial correlation of cities, as follows:

$$W_3 = \phi W_1 + (1 - \phi)W_2 \quad (9)$$

In Equation (9), the value of ϕ ranges from 0 to 1. Referring to the practice of Yang et al. [61], the value of ϕ is 0.5, indicating that the proportion of economic weight matrix and geographical weight matrix is 50%, respectively.

The global Moran's I and Geary's C for urban industrial agglomeration and carbon emissions are derived from the nested matrix of economic geography (W_3). As demonstrated in Table 3, these indicators for industrial agglomeration and urban carbon emissions are significant at the 1% level, indicating a notable spatial correlation between them. Hence, employing a spatial econometric model for analysis is justified.

Table 3. Moran's I and Geary's C statistics of China's industrial agglomeration and carbon emissions from 2009 to 2021.

Year	Industrial Agglomeration	Industrial Agglomeration	Carbon Emissions	Carbon Emissions
	Moran's I	Geary's C	Moran's I	Geary's C
2009	0.456 ***	0.536 ***	0.358 ***	0.661 ***
2010	0.462 ***	0.515 ***	0.356 ***	0.686 ***
2011	0.439 ***	0.522 ***	0.358 ***	0.683 ***
2012	0.429 ***	0.566 ***	0.359 ***	0.682 ***
2013	0.420 ***	0.555 ***	0.364 ***	0.677 ***
2014	0.428 ***	0.557 ***	0.324 ***	0.689 ***
2015	0.441 ***	0.537 ***	0.366 ***	0.676 ***
2016	0.486 ***	0.487 ***	0.373 ***	0.669 ***
2017	0.475 ***	0.506 ***	0.378 ***	0.670 ***
2018	0.499 ***	0.480 ***	0.370 ***	0.673 ***
2019	0.516 ***	0.461 ***	0.361 ***	0.679 ***
2020	0.518 ***	0.460 ***	0.333 ***	0.692 ***
2021	0.509 ***	0.473 ***	0.303 ***	0.706 ***

Note: *** indicates statistical significance at 1% level.

In order to further illustrate the spatial agglomeration relationship between industrial agglomeration level and carbon emissions among cities, this study draws Moran scatter plot of industrial agglomeration level and carbon emissions at three time nodes in 2009, 2015 and 2021. As shown in Figure 2, from 2009 to 2021, the number of cities with the industrial agglomeration level of “high-high” or “low-low” increased slightly, and some cities with the industrial agglomeration level of “low-low” had a trend of transformation to “high-high.” In other words, the regions with a high level of urban industrial agglomeration tend to have a high level of industrial agglomeration in their adjacent cities, and the overall positive correlation of industrial agglomeration space is improved. From 2009 to 2021, the number of cities with “high-high” carbon emissions shows a decreasing trend, and gradually shifts to the “low-low” type in the third quadrant. This shows that the agglomeration pollution of urban carbon emissions has been alleviated. The spatial correlation between industrial agglomeration level and carbon emissions is verified again.

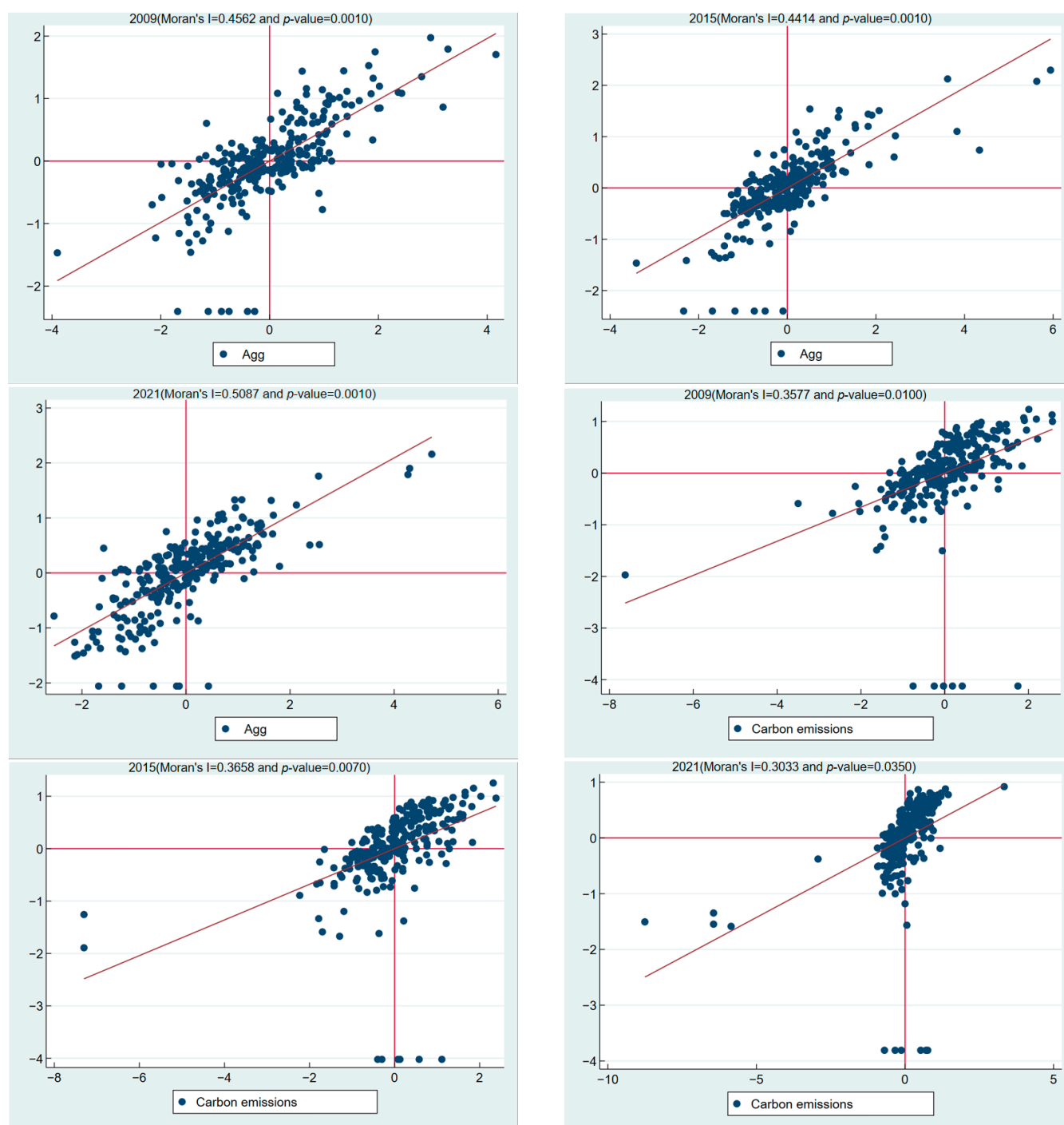


Figure 2. Scatter plot of Moran index of industrial agglomeration and carbon emissions (2009, 2015, 2021).

4.3. Model Selectivity Test

There are three considerations when selecting spatial econometric models: first, determining whether the spatial Durbin model can simplify into either a spatial error model or a spatial lag model; second, choosing between fixed and random effects; and third, assessing whether panel data necessitate dual-fixed effects over time and space. In this study, the LM test, Hausman test and joint significance test are employed to evaluate these factors and identify the most suitable spatial econometric model. As depicted in Table 4, all statistical p -values from the four LM tests are below 0.01. Consequently, the hypothesis that the spatial Durbin model can simplify into a spatial lag or error model is rejected,

suggesting that the spatial Durbin model is the most appropriate choice for the empirical analysis conducted in this study.

Table 4. Model selection test.

Inspection Method	Statistic	<i>p</i> -Value
LM inspection—Spatial lag	219.348 ***	0.000
Robust LM inspection—Spatial lag	54.100 ***	0.000
LM inspection—Spatial error	876.211 ***	0.000
Robust LM inspection—Spatial error	710.964 ***	0.000

Note: *** indicates statistical significance at 1% level.

After the LM test initially determines the spatial Durbin model, this study further tests the robustness and specific form selection of the model. The *p*-value of the Wald test and LR test in Table 5 is less than 0.01, which indicates that the hypothesis that the SDM model degenerates into the SLM or SEM model is rejected at the 1% level, again verifying the robustness of selecting the SDM model. The Hausman test *p*-value less than 0.01 indicates that the random effect model is rejected, and the specific form of fixed effect needs to be further selected. The corresponding *p*-values of the LR statistics of the individual fixed effect and the LR statistics of the time fixed effect are both less than 0.01, so the hypothesis that the two fixed effects do not exist is rejected.

Table 5. SDM model robustness and specific form tests.

Inspection Method	Statistic	<i>p</i> -Value
Wald inspection—Spatial lag	33.29 ***	0.000
Wald inspection—Error lag	74.61 ***	0.000
LR inspection—Spatial error	70.32 ***	0.000
LR inspection—Error error	3237.93 ***	0.000
Hausman test	498.50	0.000
LR Individual fixed effects test	57.55 ***	0.000
LR Time fixed effects test	95.24 ***	0.000

Note: *** indicates statistical significance at 1% level.

4.4. Model Design

4.4.1. Benchmark Regression Model

The model of the impact of industrial agglomeration on urban carbon emissions constructed in this study is as follows:

$$\text{CO}_2 = \alpha_0 + \rho_0 \sum_{i=1}^n W_{ij} \text{CO}_{2it} + \beta_1 \text{Agg}_{it} + \gamma_1 \sum_{i=1}^n W_{ij} \text{Agg}_{it} + \beta_2 \text{Agg}_{it}^2 + \gamma_2 \sum_{i=1}^n W_{ij} \text{Agg}_{it}^2 + \sigma \sum \text{Control}_{it} + \tau \sum_{i=1}^n W_{ij} \text{Control}_{it} + \delta_i + \theta_t + \varepsilon_{it} \quad (10)$$

where *i* represents the city and *t* represents the year. Controls represents a set of control variables. ε_{it} is the error term. W_{it} represents the spatial weight matrix. δ_i is the individual-fixed effect. θ_t represents time-fixed effects. α_0 represents the constant term. β_1 , β_2 and σ are the coefficients to be estimated. ρ_0 , γ_1 , γ_2 and τ are the spatial effect coefficients of the explained, explanatory and control variables, respectively. The other parameters have the same meaning as the general model above.

4.4.2. Mediating Effect Model

In order to investigate the influence mechanism of industrial agglomeration on urban carbon emissions, in this study, the spatial Durbin model is combined with the three-step

method of mediating effect to carry out stepwise regression. On the basis of Equation (10), the mediating effect model is as follows:

In the first stage, we examine the effects of industrial agglomeration on potential mediating variables as follows:

$$\text{Mediate}_{it} = \alpha_1 + \rho_1 \sum_{i=1}^n W_{ij} \text{Mediate}_{it} + \eta_1 \text{Agg}_{it} + \xi_1 \sum_{i=1}^n W_{ij} \text{Agg}_{it} + \eta_2 \text{Agg}_{it}^2 + \xi_2 \sum_{i=1}^n W_{ij} \text{Agg}_{it}^2 + \vartheta \sum_{i=1}^n \text{Control}_{it} + \sum_{i=1}^n W_{ij} \text{Control}_{it} + \delta_i + \theta_t + \varepsilon_{it} \quad (11)$$

In the second stage, we examine the effects of mediating variables on urban carbon emissions through the following formula:

$$CO_{2it} = \alpha_2 + \rho_2 \sum_{i=1}^n W_{ij} CO_{2it} + \psi_1 \text{Agg}_{it} + \omega_1 \sum_{i=1}^n W_{ij} \text{Agg}_{it} + \psi_2 \text{Agg}_{it}^2 + \omega_2 \sum_{i=1}^n W_{ij} \text{Agg}_{it}^2 + \psi_3 \text{Mediate}_{it} + \omega_3 \sum_{i=1}^n W_{ij} \text{Mediate}_{it} + \phi \sum_{i=1}^n \text{Control}_{it} + \kappa \sum_{i=1}^n W_{ij} \text{Control}_{it} + \delta_i + \theta_t + \varepsilon_{it} \quad (12)$$

On the premise that both η and ξ are significant, continue to compare the regression coefficients of Equations (12) and (10). If both ψ and ω are significant and lower than β and γ in Equation (10), it indicates that there is a partial mediating effect. If ψ_1 , ψ_2 , ω_1 and ω_2 are not significant but ψ_3 and ω_3 are significant, it indicates that there is a complete mediating effect.

5. Empirical Analysis

5.1. The Baseline Regression Result

Although it has been proved that the SDM model is more suitable for empirical research, this study still presents the results of the OLS model, SLM model and SEM model to play an auxiliary role in the benchmark regression analysis. The results are shown in Table 6.

Table 6. Model regression results.

Variable	OLS	SLM	SEM	SDM
Agg	0.980 *** (0.011)	0.924 *** (0.013)	0.971 *** (0.011)	0.974 *** (0.014)
Agg ²	−0.847 *** (0.010)	−0.799 *** (0.011)	−0.839 *** (0.010)	−0.787 *** (0.012)
pop	−3.416 *** (0.040)	−3.222 *** (0.044)	−3.388 *** (0.039)	−3.218 *** (0.050)
rgdp	1.625 *** (0.020)	1.531 *** (0.022)	1.608 *** (0.020)	1.497 *** (0.024)
scal	−0.001 (0.004)	−0.000 (0.003)	0.001 (0.003)	−0.000 (0.006)
ele	0.151 *** (0.025)	0.136 *** (0.023)	0.151 *** (0.025)	0.167 *** (0.033)
enter	1.394 *** (0.138)	1.351 *** (0.126)	1.430 *** (0.138)	1.958 *** (0.213)
W × Agg				0.116 ** (0.058)
W × Agg ²				−0.114 ** (0.051)
W × pop				−0.288 (0.205)
W × rgdp				0.263 *** (0.099)
W × scal				−0.005 (0.026)
W × ele				0.115 (0.077)
W × enter				−0.988 *** (0.383)
constant	8.379 *** (0.922)			
Ind-fixed effect	YES	YES	YES	YES
Time-fixed effect	YES	YES	YES	YES
$\rho_{(\lambda)}$		0.183 *** (0.024)	0.175 *** (0.042)	0.124 *** (0.043)
Sigma		0.146 *** (0.003)	0.148 *** (0.004)	0.148 *** (0.004)
R ²	0.794	0.230	0.824	0.250
N	3640	3640	3640	3640

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

The empirical results reveal that industrial agglomeration's effect on urban carbon emissions is significant at the 1% level, with a positive coefficient for the primary term and a negative one for the quadratic term. This indicates a non-linear, inverted U-shaped relationship. Additionally, the spatial spillover effects of both terms on urban carbon emissions are significant at the 5% level, further supporting the inverted U-shaped pattern. These findings align with the conclusions of [30]. At the same time, this conclusion contradicts a series of studies that support the view of environmental degradation [8,9] or environmental improvement [10,11], which suggest that industrial agglomeration has a single linear effect on urban carbon emissions. The results show that low industrial agglomeration has a significant spatial spillover effect while increasing local carbon emissions. With the improvement in industrial agglomeration level, it gradually promotes the reduction in carbon emissions in the region and neighboring cities. This result proves Hypothesis 1. The economic significance of this conclusion may lie in the fact that, in the early stage of industrial agglomeration, a large number of enterprises poured into the agglomeration area, many of which were traditional manufacturing industries with high energy consumption and high emissions. This rapid economic growth and urbanization process has led to a rapid rise in energy demand, increasing carbon emissions. As the economy of the agglomeration area matures, enterprises turn to low-carbon and green technologies, improving energy efficiency and reducing carbon emissions per unit of output. Moreover, environmental policies have become more stringent, using market instruments (carbon trading) and administrative measures (emission standard setting) to encourage enterprises in the cluster to adopt more environmentally friendly production methods. Agglomeration and neighboring regions often achieve coordinated emission reductions through regional cooperation policies, thus achieving an overall reduction in emissions on a wider geographical scale.

5.2. Spatial Matrix Sensitivity Analysis Results

This study conducts a sensitivity analysis of the spatial matrix to validate the scientific and rational application of spatial econometric regression analysis using an economic geographic weight matrix. The procedure involves employing the spatial Durbin model to perform regressions with a geographical distance matrix (W_1) and an economic distance matrix (W_2) individually. The results are then compared with those obtained using the economic geography nested matrix (W_3). The findings from the sensitivity analysis of the spatial matrix are presented in Table 7.

Table 7. Sensitivity analysis of spatial matrix selection.

Variable	W_1	W_2	W_3
Agg	0.977 *** (0.012)	1.489 *** (0.537)	0.974 *** (0.014)
Agg ²	−0.831 *** (0.008)	−0.821 * (0.429)	−0.787 *** (0.012)
pop	−3.353 *** (0.039)	0.009 (0.019)	−3.218 *** (0.050)
rgdp	1.592 *** (0.020)	−0.039 *** (0.014)	1.497 *** (0.024)
scal	0.001 (0.004)	−0.0012 (0.013)	−0.000 (0.006)
ele	0.153 *** (0.025)	0.345 *** (0.068)	0.167 *** (0.033)
enter	1.677 *** (0.138)	0.407 (0.389)	1.958 *** (0.213)
$W \times \text{Agg}$	0.513 ** (0.143)	0.592 *** (0.104)	0.116 ** (0.058)
$W \times \text{Agg}^2$	−0.498 *** (0.051)	−0.195 ** (0.075)	−0.114 ** (0.051)
$W \times \text{pop}$	−1.795 (0.510)	0.001 (0.028)	−0.288 (0.205)
$W \times \text{rgdp}$	1.089 *** (0.244)	−0.014 (0.027)	0.263 *** (0.099)
$W \times \text{scal}$	0.038 (0.050)	0.032 (0.034)	−0.005 (0.026)
$W \times \text{ele}$	−0.892 ** (0.375)	0.171 (0.132)	0.115 (0.077)
$W \times \text{enter}$	1.677 *** (0.138)	0.372 (0.709)	−0.988 *** (0.383)

Ind-fixed effect	YES	YES	YES
Time-fixed effect	YES	YES	YES
ρ (λ)	0.173 *** (0.024)	0.175 *** (0.042)	0.124 *** (0.043)
Sigma	0.156 *** (0.003)	0.148 *** (0.004)	0.148 *** (0.004)
R ²	0.173	0.124	0.250
N	3640	3640	3640

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

The sensitivity analysis results indicate significant regression coefficients and spatial spillover effects of industrial agglomeration when applying the geographic matrix (W_1) and economic distance matrix (W_2). However, the R^2 values for regressions using the geographic distance matrix (W_1) and economic distance matrix (W_2) are lower compared to those using the economic geographic nested weight matrix (W_3). This shows that the goodness of fit of the model is higher when the economic geographic weight matrix is used for regression. It can be proved that it is reasonable to choose economic geographical weight matrix as the matrix of spatial econometric model in this study.

5.3. Spatial Effect Decomposition

In order to further reveal the direct impact and spillover effects of industrial agglomeration on urban carbon emissions, this study further decomposed the spatial effects of the SDM model with the partial differential method, and demonstrated the direct, indirect and overall effects of the SDM model. The direct effect represents the influence of various influencing factors on carbon emissions in the region, and the indirect effect represents the influence of regional influencing factors on carbon emissions in neighboring regions. The total effect is the sum of the two, representing the overall impact of the factors in the region on carbon emissions in all regions. The decomposition results are shown in Table 8.

Table 8. Spatial effect decomposition results.

Variable	Direct Effect	Indirect Effect	Total Effect
Agg	0.992 *** (0.011)	0.100 *** (0.016)	1.092 *** (0.020)
Agg ²	−0.857 *** (0.009)	−0.087 *** (0.014)	−0.944 *** (0.018)
pop	−3.469 *** (0.039)	−0.387 *** (0.057)	−3.856 *** (0.069)
rgdp	1.639 *** (0.019)	0.119 *** (0.029)	1.758 *** (0.036)
scal	0.002 (0.004)	0.004 (0.010)	0.006 (0.012)
ele	0.140 *** (0.025)	0.069 * (0.041)	0.209 *** (0.053)
enter	1.650 *** (0.132)	0.820 *** (0.216)	2.470 *** (0.249)

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

Analyzing the decomposition of the spatial spillover effect reveals that both the direct and indirect effects, as well as the total impact of industrial agglomeration's primary and quadratic terms, exhibit consistent signs: positive for the primary term and negative for the quadratic term. The significance test confirms that industrial agglomeration's impact on urban carbon emissions—locally, in neighboring areas and across all regions—follows an inverted U-shaped trajectory, initially enhancing emissions before subsequently reducing them. This indicates a pronounced spatial spillover effect. During the initial phases of industrial agglomeration, the concentration level is modest, primarily attracting low-end industries characterized by high energy consumption and pollution, thereby elevating urban carbon emissions and worsening environmental conditions in nearby cities. This pattern aligns with the prevalent developmental concept of prioritizing economic growth over environmental protection, with remediation postponed. As industrial agglomeration intensifies, competition spurs technological innovation within firms, leading to enhanced

resource efficiency and a decline in carbon emissions per unit of output. Moreover, the high concentration of interconnected enterprises facilitates collaborative pollution management, lowering associated costs. At this juncture, the beneficial externalities of industrial agglomeration on carbon emissions underscore a significant spatial spillover effect, contributing to an overall decrease in emissions. This evidence supports the validity of Hypothesis 1.

5.4. Robustness Test Result

In order to validate the scientific rigor and logical soundness of the empirical findings mentioned above, this study undertakes the following robustness checks: first, the economic geography nested matrix ($W_1 \times W_2$) is replaced by the economic geography weight matrix. Second, referring to the practice of Yan et al. [62], the nearest railway mileage between cities is used to replace the surface distance between cities, and a new nested matrix of economic geography is constructed. The construction steps are consistent with the spatial nested matrix. Thirdly, we refer to the range emission method of Cong et al. [63] to calculate urban carbon emissions to replace the explained variable. Lastly, this study refers to the practice of Yang et al. [64], replacing the calculation method of the independent variable. The number of urban employment (10,000 people) is divided by the administrative area (square kilometers), instead of the location entropy method to estimate the level of industrial agglomeration. We employed the same spatial Durbin model to evaluate the four strategies discussed earlier, with detailed results from the robustness tests presented in Table 9.

Table 9. Robustness test results.

Variable	Economic Geography Weight Matrix	The Reconstructed Nested Matrix of Economic Geography	Replace the Dependent Variable	Replace the Independent Variable
Agg	1.113 *** (0.012)	0.969 *** (0.009)	1.491 *** (0.536)	1.003 *** (0.013)
Agg ²	−0.891 *** (0.011)	−0.837 *** (0.010)	−0.721 * (0.377)	−0.863 *** (0.011)
pop	−3.623 *** (0.044)	−3.379 *** (0.040)	0.009 (0.019)	−3.493 *** (0.046)
rgdp	1.685 *** (0.022)	1.611 *** (0.019)	−0.039 *** (0.014)	1.636 *** (0.023)
scal	0.003 (0.004)	0.003 (0.002)	−0.001 (0.013)	0.002 (0.004)
ele	0.113 *** (0.025)	0.156 *** (0.025)	0.345 *** (0.068)	0.146 *** (0.025)
enter	1.976 *** (0.166)	1.379 *** (0.145)	0.407 (0.389)	1.586 *** (0.174)
W × Agg	0.252 *** (0.028)	0.115 *** (0.040)	0.581 *** (0.104)	0.165 *** (0.031)
W × Agg ²	−0.218 *** (0.024)	−0.097 *** (0.035)	−0.194 ** (0.075)	−0.142 *** (0.026)
W × pop	−0.932 *** (0.097)	−0.398 *** (0.143)	0.001 (0.028)	0.596 *** (0.106)
W × rgdp	0.359 *** (0.049)	0.179 ** (0.071)	−0.014 (0.027)	−0.219 *** (0.052)
W × scal	−0.005 (0.012)	0.009 (0.011)	0.032 (0.034)	0.004 (0.011)
W × ele	−0.071 (0.049)	−0.132 (0.089)	0.153 (0.135)	0.094 * (0.048)
W × enter	1.245 *** (0.276)	0.146 (0.296)	0.412 (0.709)	−1.152 *** (0.268)
Ind-fixed effect	YES	YES	YES	YES
Time-fixed effect	YES	YES	YES	YES
$\rho (\lambda)$	0.125 *** (0.020)	0.067 * (0.034)	0.107 *** (0.023)	0.060 *** (0.022)
Sigma	0.142 *** (0.004)	0.160 *** (0.038)	0.314 *** (0.012)	0.135 *** (0.004)
R ²	0.825	0.804	0.157	0.817
N	3640	3640	3640	3640

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

Regardless of whether the matrix or the core variable is altered, the inverted U-shaped effect of industrial agglomeration on urban carbon emissions remains consistent, with minimal variation. This stability further validates the scientific basis for using the

spatial Durbin model in our estimations, as well as the rationale behind the inverted U-shaped impact observed.

5.5. Endogeneity Test

Urban carbon emissions could negatively influence the development trajectory of industrial agglomeration. The presence of bidirectional causality may result in endogeneity issues. To address the endogeneity arising from omitted variables and reverse causality, the instrumental variable approach (2SLS) was employed for testing. In regression models that include endogenous variables and their quadratic terms, it is common practice to conduct instrumental variable tests using one instrumental variable and its quadratic term. This study considers that optimizing the business environment promotes the facilitation of various industries and drives the development of industrial agglomeration. But the quality of the business environment does not have a direct impact on urban emissions. This study innovatively selects the business environment index (*envir*) and its quadratic term (*envir*²) of prefecture-level cities as instrumental variables. The specific measurement method of the index refers to the research of Yang et al. [65]. The test results are shown in Table 10.

Table 10. Endogeneity test.

Variables	The First Stage		The Second Stage
	(1) <i>envir</i>	(2) <i>envir</i> ²	(3) CO ₂
Agg	0.231 *** (0.019)	0.260 *** (0.022)	1.066 *** (0.075)
Agg ²	0.027 *** (0.002)	0.031 *** (0.003)	−0.919 *** (0.065)
Control	YES	YES	YES
Ind-fixed effect	YES	YES	YES
Time-fixed effect	YES	YES	YES
N	3640	3640	3640
R ²	0.591	0.566	0.845
F	748.01 ***	674.89 ***	989.85 ***
Unidentifiable test			63.724 ***
Weak instrumental variable test			32.351 ***

Note: *** indicates statistical significance at 1% level.

Columns (1)–(2) show that endogenous variables have a significant impact on instrumental variables in the first-stage estimation. The results of column (3) show that the instrumental variable passes the unidentifiable test and weak instrumental variable test. The 2SLS method is used for estimation. The impact of the primary term and the secondary term of the industrial agglomeration level on carbon emissions is still significant and basically consistent with the benchmark regression results.

5.6. Mediating Effect Test

Green technology innovation and green talent agglomeration are used as mediating variables for further regression. The regression results are shown in Table 11.

Table 11. Regression results of the mediation model.

Variable	(1)	(2)	(3)	(4)
	GTI	Carbon Emission	STA	Carbon Emission
Agg	−0.084 *** (0.002)	1.035 *** (0.012)	−0.021 *** (0.002)	0.865 *** (0.013)
Agg ²	0.066 *** (0.014)	−0.884 *** (0.011)	0.037 *** (0.003)	−0.763 *** (0.011)
GTI		−0.044 *** (0.015)		
STA				−0.037 ** (0.017)
pop	−0.303 *** (0.057)	−3.638 *** (0.044)	0.018 (0.013)	−3.492 *** (0.047)

rgdp	0.179 *** (0.029)	1.694 *** (0.022)	−0.005 (0.010)	1.635 *** (0.024)
scal	−0.016 *** (0.006)	−0.003 (0.004)	0.016 ** (0.008)	−0.007 (0.007)
ele	−0.058 * (0.033)	0.110 *** (0.025)	0.152 *** (0.043)	0.292 *** (0.036)
enter	1.470 *** (0.218)	2.043 *** (0.168)	0.566 ** (0.243)	2.197 *** (0.202)
W × Agg	−0.021 * (0.011)	0.247 *** (0.028)	−0.011 *** (0.004)	0.085 *** (0.030)
W × Agg ²	0.023 * (0.013)	−0.212 *** (0.024)	0.097 ** (0.024)	−0.069 * (0.035)
W × GTI		−0.210 *** (0.026)		
W × STA				−0.161 *** (0.034)
W × pop	0.682 *** (0.103)	0.947 *** (0.098)	−0.036 * (0.020)	−0.688 *** (0.104)
W × rgdp	−0.037 (0.052)	−0.367 *** (0.049)	−0.021 (0.019)	0.277 *** (0.052)
W × scal	−0.028 * (0.016)	0.004 (0.012)	0.010 (0.021)	−0.023 (0.018)
W × ele	−0.097 (0.065)	0.071 (0.050)	0.163 * (0.084)	−0.060 (0.070)
W × enter	−0.086 (0.364)	−1.287 *** (0.279)	0.208 (0.447)	0.702 * (0.372)
Ind-fixed effect	YES	YES	YES	YES
Time-fixed effect	YES	YES	YES	YES
$\rho (\lambda)$	0.128 *** (0.025)	0.127 *** (0.019)	0.145 *** (0.032)	0.148 *** (0.021)
Sigma	0.245 *** (0.006)	0.142 *** (0.004)	0.167 *** (0.005)	0.114 *** (0.003)
R ²	0.497	0.823	0.293	0.766
N	3640	3640	3640	3640

Note: *, ** and *** indicates statistical significance at 10%, 5% and 1% levels, respectively.

First, we need to examine the effect of the independent variable on the intermediary variable. In columns (1) and (3), the influence coefficients of the primary term and the quadratic term of the industrial agglomeration level on the number of urban green innovation efficiency and the agglomeration degree of urban green talents are both significant and have spatial spillover effect. In an economic sense, in the early stage of industrial agglomeration, enterprises in the agglomeration area usually compete for limited resources. In addition, this competitive environment can lead to under-appreciated needs for environmentally friendly talent, as companies focus more on short-term economic benefits and market share than on long-term sustainability goals. In this case, environmentally friendly talents may choose to leave or be reluctant to enter the area due to the lack of suitable employment opportunities, resulting in a lower degree of talent concentration. In the later stage of agglomeration, the government may pay more attention to environmental protection, propose stricter environmental standards and encourage enterprises to carry out green transformation, thus further promoting green innovation in the region and surrounding areas. Moreover, with the implementation of environmental policies in various regions, enterprises in the cluster area have gradually realized the importance of environmentally friendly talents in sustainable development. Enterprises, scientific research institutions and government departments in various regions may establish cooperative relationships to jointly conduct environmental technology research and development and personnel training. With the formation of this cooperation network, the demand and attractiveness of environmentally friendly talents has increased significantly, further promoting the concentration of talents in the region and surrounding areas. Next, the independent variable and the mediating variable are included in the model, and the dependent variable is regressed. The coefficients for the primary term of industrial agglomeration in columns (2) and (4) remain significantly positive, while those for the quadratic term are significantly negative, confirming the original inverted U-shaped hypothesis and indicating spatial spillover effects. Integrating mediating variables into the regression model reveals that both green technology innovation and green talent agglomeration significantly inhibit urban carbon emissions and exhibit spatial spillover. These findings demonstrate that these green factors substantially lower urban carbon emissions locally and in neighboring areas. A comparison of regression coefficients reveals that, in columns (2) and (4) of Table 11, the absolute values of coefficients for both primary and quadratic terms of

industrial agglomeration are less than those in Table 6, indicating a partial mediating effect of the tested variables. Thus, the results suggest that the inverted U-shaped impact of industrial agglomeration on urban carbon emissions is partially mediated by urban green technology innovation and green talent agglomeration. In the early stage of industrial agglomeration, carbon emissions rose due to the high intensity of energy consumption and the inability of infrastructure to meet the needs of rapid development. However, with the introduction and development of green innovation and green talents, the growth rate of carbon emissions is gradually slowed down in the middle stage, and carbon emissions are significantly reduced in the later stage, forming an inverted U-shaped trend. This process is not only dependent on technological progress and talent leadership, but also closely related to the government's tax relief, innovation incentive policy guidance and the active transformation of enterprises in the cluster area. Hypotheses 2 and 3 are verified.

5.7. Analysis of Heterogeneity

(1) Heterogeneity tests based on geographic region. The terrain of our country presents the features of a ladder. Geographical differences may lead to certain differences in the policy orientation, resource endowment and industrial structure of different cities. Under the condition of economic geography nested matrix (W_3), this study conducts regression according to the eastern, central and western regions. The results are shown in Table 12.

Table 12. Geographical heterogeneity test.

Variable	East	Middle	West
Agg	0.936 *** (0.018)	0.697 *** (0.014)	0.122 (0.184)
Agg ²	−0.800 *** (0.016)	−0.489 *** (0.010)	−0.106 (0.161)
pop	−3.277 *** (0.063)	−0.034 ** (0.125)	0.417 (0.673)
rgdp	1.539 *** (0.033)	−0.562 *** (0.095)	0.417 *** (0.067)
scal	0.154 ** (0.069)	−0.059 (0.079)	0.002 (0.003)
ele	0.201 *** (0.064)	0.034 (0.070)	0.088 *** (0.024)
enter	1.588 *** (0.234)	−0.565 *** (0.207)	−0.736 (0.943)
W × Agg	0.285 *** (0.070)	0.800 *** (0.224)	0.067 (0.115)
W × Agg ²	−0.069 (0.060)	−0.500 *** (0.163)	0.049 (0.099)
W × pop	0.305 *** (0.024)	−0.616 *** (0.200)	0.555 (0.388)
W × rgdp	−0.945 *** (0.122)	−4.982 *** (1.243)	−0.0944 (0.184)
W × scal	0.125 (0.201)	0.069 (0.424)	−0.001 (0.006)
W × ele	0.100 (0.156)	−0.922 ** (0.451)	0.249 *** (0.084)
W × enter	−0.586 (0.464)	−1.290 (2.900)	2.862 (2.631)
Ind-fixed effect	YES	YES	YES
Time-fixed effect	YES	YES	YES
$\rho_{(\lambda)}$	0.571 *** (0.049)	1.191 *** (0.267)	0.037 (0.063)
Sigma	0.303 *** (0.012)	0.296 *** (0.013)	0.077 *** (0.004)
R ²	0.661	0.354	0.190
N	1300	1300	1040

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

In both the eastern and central regions, the coefficients for the primary and quadratic terms of industrial agglomeration level are significant at the 1% level concerning urban carbon emissions. However, the spatial spillover effect of the quadratic term in the eastern region is not significant. This indicates that, as industrial agglomeration advances in the eastern region, it continues to contribute to rising carbon emissions in neighboring areas. The government has adopted preferential policies for the eastern region to encourage investment by enterprises of all parties, attracting a large amount of capital. However, due

to the lack of perfect environmental compensation mechanism, the environmental improvement in the eastern region is not as strong as that of the central region [66]. The spatial spillover effects of industrial agglomeration in the central region on urban carbon emissions are all significant at the significance level of 1%. The inverted “U” shape assumption is satisfied. This shows that factors such as the industrial nature in the central region lead to the spatial spillover of carbon emissions in the early stage of industrial agglomeration in the central region. With the improvement in industrial agglomeration level, the efficiency of factor allocation within clusters in the central region has improved. It has a technology spillover effect on the surrounding cities. Therefore, the surrounding cities are promoted to reduce carbon emissions. Whether it is the local effect or the spatial spillover effect, the regression coefficient of industrial agglomeration in western cities is not significant. This is consistent with the conclusions of Yuan et al. [67]. This result may be due to the following reasons. On one hand, the western region is complex and far from trading ports. As a result, most enterprises do not choose to invest and build factories there, which makes the industrial agglomeration scale in the western region far smaller than that in the central and eastern regions, and does not have a profound impact on urban carbon emissions. On the other hand, the gap between the economic base of western cities is too large. For example, most cities in Xinjiang, Qinghai and Gansu are quite different from Chengdu and Chongqing. As a result, there are also large differences in the production mode and scientific and technological level of cities, and the concept of green development will also be different. They choose different ways to deal with pollution.

(2) Heterogeneity analysis based on urban development characteristics: variations in urban resource endowment influence the level of industrial agglomeration and subsequently affect a city’s carbon emissions. Following the National Sustainable Development Plan for Resource-based Cities (2013–2020), this study categorizes the sample of prefecture-level cities into resource-based and non-resource-based. From the perspective of resource endowment, we examine how industrial agglomeration differently impacts urban carbon emissions. The findings are presented in columns (1) and (2) of Table 13.

Table 13. Heterogeneity test of urban resources.

Variable	(1) Non-Resource-Based Cities	(2) Resource-Based Cities	(3) Non-Old Industrial Cities	(4) Old Industrial Cities
Agg	1.118 *** (0.014)	0.705 *** (0.088)	1.135 *** (0.012)	0.679 *** (0.127)
Agg ²	−0.824 *** (0.010)	0.107 (0.154)	−0.884 *** (0.011)	0.117 (0.154)
pop	−3.940 *** (0.125)	−0.419 (0.643)	−3.638 *** (0.044)	−0.101 (0.204)
rgdp	1.922 *** (0.095)	0.206 *** (0.031)	1.694 *** (0.022)	−0.305 (0.194)
scal	−0.001 (0.079)	0.001 (0.003)	−0.000 (0.004)	0.339 *** (0.116)
ele	0.092 *** (0.070)	0.084 *** (0.023)	0.110 *** (0.025)	0.211 * (0.109)
enter	−4.176 *** (0.207)	−0.680 (0.913)	2.043 *** (0.168)	−0.647 * (0.391)
W × Agg	0.471 *** (0.109)	0.377 ** (0.191)	0.247 *** (0.028)	0.365 (0.291)
W × Agg ²	−0.373 *** (0.095)	−0.103 (0.413)	−0.212 *** (0.024)	−0.051 (0.048)
W × pop	−1.691 *** (0.379)	−0.140 (0.407)	0.947 *** (0.098)	0.935 * (0.544)
W × rgdp	0.404 *** (0.171)	0.655 *** (0.187)	−0.367 *** (0.049)	−0.911 ** (0.374)
W × scal	0.013 * (0.007)	0.008 (0.006)	0.004 (0.012)	−0.231 (0.346)
W × ele	0.170 * (0.095)	0.202 * (0.089)	0.071 (0.050)	0.034 (0.265)
W × enter	5.019 ** (2.381)	0.482 (2.579)	−1.287 *** (0.279)	0.028 (0.734)
Ind-fixed effect	YES	YES	YES	YES
Time-fixed effect	YES	YES	YES	YES
$\rho_{(\lambda)}$	0.633 *** (0.064)	0.149 (0.671)	0.127 *** (0.019)	0.226 *** (0.435)
Sigma	0.101 *** (0.004)	0.873 *** (0.034)	0.142 *** (0.004)	0.874 *** (0.034)
R ²	0.778	0.115	0.823	0.105

N	2236	1404	1235	2405
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Note: *, ** and *** indicate statistical significance at 10%, 5% and 1% levels, respectively.

In non-resource-based cities, industrial agglomeration exhibits a clear inverted U-shaped correlation with a spatial spillover effect on carbon emissions. Conversely, resource-based cities remain in a phase wherein carbon emissions are intensifying, accompanied by spatial spillover effects. The later stages of industrial agglomeration in resource-based cities do not significantly contribute to emission reduction. In resource-based cities, industrial agglomeration is usually concentrated in high energy consumption and high pollution industries such as exploitation and primary processing of natural resources [9]. Because these industries rely on the in situ use of resources, it is difficult to achieve significant improvements in energy efficiency or effective control of pollution through technological innovation in a short time. This special industrial structure makes the industrial agglomeration of resource-based cities directly lead to the increase in carbon emissions. Not only will emissions increase in the region due to the agglomeration of highly polluting industries, but the surrounding regions may also experience an increase in carbon emissions due to transport entry, expansion of supporting industries and pollution transfer. In contrast, in non-resource-based cities, industrial agglomeration may involve more diversified and technology-intensive industries. With the deepening of agglomeration degree, carbon emissions showed an upward trend at the beginning due to the scale effect and the increase in economic activities. However, when the economy reaches a certain scale, enterprises may be more inclined to adopt clean technologies and more efficient management modes in order to reduce costs and improve efficiency, so as to achieve the reduction in carbon emissions, that is, an inverted U-shaped trend.

The characteristics of industrial structures significantly influence urban environmental stress. This study explores the varying effects of industrial agglomeration on the carbon emissions of both old industrial and non-old industrial cities. The findings are detailed in columns (3) and (4) of Table 13. Initially, industrial agglomeration exacerbates carbon emissions in non-old industrial cities. However, as agglomeration progresses, it gradually carbon curbs emissions in these cities, exhibiting an inverted U-shaped pattern and a spatial spillover effect. In contrast, for old industrial cities, agglomeration continues to increase carbon emissions without any spatial spillover present. Due to historical reasons, old industrial bases may lag behind other regions in terms of technological upgrading, and even if there is capital accumulation, this capital may be used more for maintaining the operation of existing facilities than for technological upgrading [68]. In this way, industrial agglomeration does not bring about effective carbon efficiency improvement; on the contrary, the concentrated use of old equipment and processes increases the carbon emission burden. Moreover, due to the inherent economic influence of the old industrial base cities, the spillover of the industrial chain often drives the joint development of the surrounding areas, but it also leads to the diffusion of pollutants and carbon emissions. In contrast, industrial agglomeration in non-old industrial cities may involve more environmental protection technology and service industries. With the expansion of economic scale, they have more ability and motivation to improve technology, improve production efficiency, and achieve effective control of carbon emissions, thus reflecting the inverted U-shaped trend in the process of industrial agglomeration.

6. Discussion and Conclusions

6.1. Discussion

First, the current study finds that industrial agglomeration has a significant inverted U-shaped impact on urban carbon emissions, with distinct spatial spillover effects. Although Li et al. [30] also put forward the same conclusion, they only considered the macro provincial perspective and could not offer an accurate account for the urban circum-

stances. This study presents a new standpoint from the urban dimension. Due to the competition effect and green technology spillover effect in inter-city industrial development, industrial agglomeration has a patently inverted U-shaped tie with spatial spillover impact on urban carbon emissions. It is desirable to facilitate the formation of energy conservation and emission reduction policy coordination mechanism among cities, so as to promptly help cities cross the inverted U-shaped turning point and achieve emission reduction targets.

Second, the current transmission mechanism of industrial agglomeration impacting carbon emissions mostly centers on traditional technological innovation [30] and foreign investment [69]. But compared with traditional technology innovation, enterprise green innovation has both green and innovative dual concepts. It reflects the win-win effect of industrial development on urban environmental performance and economic performance. Compared with foreign investment, green innovation efficiency and green talent concentration can better reflect the output results of urban green innovation. This study finds that industrial agglomeration not only has a reversed U-shaped effect on carbon emissions, but also indirectly affects carbon emissions by improving the efficiency of urban green innovation and the concentration of green talents. To broaden the current transmission mechanism of industrial agglomeration will affect carbon emissions and achieve deeper knowledge about the relationship between them.

Third, like most previous studies, this study also divides China into three geographical areas: east, middle and west, and explores the diverse relationships between industrial agglomeration and urban carbon emissions [69]. As a matter of fact, the relationship between industrial agglomeration and carbon emissions suggests that differences between cities with various types of industrial structures and resource endowments are much greater than their geographical divergences [68]. Thus, the contrastive analysis grounded on various industrial structure types and resource endowment types has far more practical guiding significance.

6.2. Conclusions

This study utilizes panel data from 280 Chinese prefecture-level cities covering the years from 2009 to 2021, applying the spatial Durbin model to explore the effects of industrial agglomeration on urban carbon emissions and its mechanisms, and draws the following conclusions:

First, industrial agglomeration and urban carbon emissions in Chinese cities exhibit notable spatial correlations. These relationships reflect “high-high” and “low-low” spatial clustering patterns, with urban carbon emissions gradually transitioning from “high-high” to “low-low” clustering. Based on empirical findings from 280 prefecture-level cities in China, industrial agglomeration has an inverted U-shaped effect on urban carbon emissions and neighboring cities. Initially, industrial agglomeration leads to increased carbon emissions in both local and surrounding areas. However, as industrial agglomeration intensifies, it begins to limit carbon emissions within these areas.

Second, the relationship between industrial agglomeration and urban carbon emissions varies by region in Chinese cities, with differing spatial spillover effects. This regional heterogeneity is distinct: in the eastern and central regions, industrial agglomeration levels have an inverted U-shaped association with regional carbon emissions, while in the western region, this relationship is insignificant. The spatial spillover effect also varies by region; in the eastern and western regions, the reduction effect on surrounding areas’ carbon emissions is minimal, whereas in the central region, industrial agglomeration often surpasses the inverted U-shaped threshold, leading to significant reductions in surrounding areas’ carbon emissions.

Third, the inherent differences in the urban resource foundations contribute to the heterogeneity in the impact of industrial agglomeration on carbon emissions. In non-resource-based cities, industrial agglomeration impacts carbon emissions in an inverted U-

shaped manner, while in resource-based cities, it generally leads to an increase in emissions. Regarding spatial spillover effects, industrial agglomeration in non-resource-based cities has an inverted U-shaped impact on the emissions of surrounding cities. In contrast, in resource-based cities, it tends to exacerbate emissions in neighboring areas. Additionally, in non-old industrial cities, industrial agglomeration follows an inverted U-shaped trend with carbon emissions, whereas in old industrial cities, it intensifies regional carbon emissions.

Fourth, industrial agglomeration fosters green technology innovation and talent agglomeration. On one hand, the rising level of agglomeration enhances both urban green technology innovation and talent agglomeration, which in turn help to curb carbon emissions. Clearly, green innovation and the concentration of green talent serve as key intermediaries in the inverted U-shaped connection between industrial agglomeration and urban carbon emissions. Thus, the advancement of urban green technology driven by industrial agglomeration acts as a crucial catalyst for sustainable urban development.

6.3. Recommendations

Based on the above conclusions, this study proposes the following policy-making suggestions for relevant Chinese governmental authorities:

First, in the early stage of industrial agglomeration, the industrial and environmental authorities should optimize the layout of urban industries and the plan of the boundary of industrial development. Industrial development should give full play to synergistic effects of agglomeration, while accelerating the breakthrough of the critical point of industrial agglomeration from aggravating pollution to curbing carbon emissions. When the level of industrial agglomeration has significantly improved, the governments should avoid the homogeneous competition of industrial clusters caused by limited resources to reduce the negative impact of inefficient production capacity on regional carbon emissions. In terms of policies, the eastern region should be encouraged to transfer energy-intensive and high-polluting industries to neighboring regions or central and western regions, and promote the concentrated development of green and low-carbon industries through tax incentives, land policy support and other means to reduce the pressure on carbon emissions in neighboring regions.

Second, the governments should take measures in light of local conditions, rationally allocate technology and capital development factors and pursue regional characteristics of the industrial agglomeration path. The eastern region should rely on its advantages of factor agglomeration in geographical location, talent capital and market technology, so as to break the barriers of factor flow between regions. By contrast, the central and western regions should actively develop regionally characteristic industries based on their own advantages in the cost of factors such as resources, land and labor. Meanwhile, the governments should focus on solving problems, such as single industry and resource curse, while making efforts to cultivate the mechanism of industrial agglomeration in the western region to inhibit carbon emissions. In particular, the government should promote the reform of the energy market in the western region and establish a renewable energy consumption quota system in the industrial agglomeration area to promote green production. At the same time, carbon financial services should be provided to encourage enterprises in the western industrial clusters to reduce carbon emission costs by purchasing carbon credits.

Third, in line with the different developmental characteristics and basis of each city, the governments should guide the reasonable agglomeration of urban industries accordingly. The governments should provide preferential policies and support measures in those resource-based cities to attract and support green industry enterprises. At the same time, it is advisable to establish a carbon emission monitoring and accounting system in those resource-based cities, in order to track the impacts of industrial agglomeration on urban carbon emissions. Those non-resource-based cities should promote the green development of surrounding areas, share resources and green technologies and promote the

formation of green industrial clusters. For the existing old industrial agglomeration areas, the governments should introduce clean production technology to improve the management level of carbon emissions. For those non-old industrial cities, digital industrial agglomeration should be developed to promote the industrial transition to high-tech and high-value-added fields and reduce carbon emissions.

Fourth, the governments should utilize industrial agglomeration to accelerate the progress level of urban green technology. The governments should provide tax relief, R&D financial support and other measures for all entities in the cluster to incentivize enterprises to invest in R&D and the application of green technologies. For example, those enterprises within the cluster that adopt clean energy should be given tax-reduction incentives. In recent years, China's green innovation efficiency has shown a slowdown, while the transformative efficiency of green achievements remains low. Thus, the governments should promote industry–university research cooperation, build a platform for technological innovation and exchange and promote the R&D and achievement conversion of green technologies. For instance, regular green technology expos, seminars and other activities should be held to promote know-how sharing and technological cooperation.

Fifth, the governments should make use of industrial agglomeration to enhance the introduction of green technology talents. The governments should formulate preferential policies to attract highly skilled talents and experts in green industries to work in industrial clusters, provide housing subsidies and research funding, set up green-talent award programs to commend individuals or teams who have made outstanding contributions to green technology innovation and environmental protection, so as to improve their social status and public influences. Meanwhile, the governments should also actively support green technology training, provide opportunities for continuing education and upskilling for in-service personnels and encourage the switch to green production fields.

6.4. Limitations and Future Directions

There are still some limitations in this study, which is also the direction of future research. First of all, the carbon emission factor plays a decisive role in urban carbon emission measurement methods. But this method assumes that the carbon emission factor of a given energy source is fixed. However, due to the differences in economic development and technical level of cities, carbon emission factors are not uniform and unchanged, which will lead to errors in measurement results. In view of the above problems, a variety of accounting methods will be used in the following research to make the results more robust and reliable. Secondly, no dummy variables are added, such as “low-carbon pilot cities” as the external impact of policies. In future studies, policies closely related to urban carbon emissions should be included in the model. Lastly, in terms of data, due to data defects and difficulties in finding them, this study only included the data of 280 prefecture-level cities in the modeling of urban spatial panel data, and did not include the data of prefecture-level cities in the model one by one. In the future research, the sample will be further expanded, or the research object will more accurately reflect the county's administrative region for specific analysis. In addition, we will further discuss whether the conclusions of this study are applicable to other rapidly industrializing countries and the nonlinear relationship between industrial agglomeration and urban carbon emissions and the relevance of global climate policy.

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References

1. Mohan, R.R. Time Series Ghg Emission Estimates for Residential, Commercial, Agriculture and Fisheries Sectors in India. *Atmos. Environ.* **2018**, *178*, 73–79.
2. Peters, G.P.; Marland, G.; Le Quéré, C.; Boden, T.; Canadell, J.G.; Raupach, M.R. Rapid Growth in CO₂ Emissions After the 2008–2009 Global Financial Crisis. *Nat. Clim. Change* **2011**, *2*, 2–4.
3. Li, Y. Path-Breaking Industrial Development Reduces Carbon Emissions, Evidence from Chinese Provinces, 1999–2011. *Energy Policy* **2022**, *167*, 113046.
4. Wang, M.; Zhang, M.; Chen, H.; Yu, D. How Does Digital Economy Promote the Geographical Agglomeration of Manufacturing Industry? *Sustainability* **2023**, *15*, 1727.
5. Liu, S.; Wu, P. The impact of high-tech industrial agglomeration on China's green innovation efficiency: A spatial econometric analysis. *Front. Environ. Sci.* **2023**, *11*, 1167918.
6. Chen, C.; Sun, Y.; Lan, Q.; Lan, Q.; Jiang, F. Impacts of Industrial Agglomeration on Pollution and Ecological Efficiency-A Spatial Econometric Analysis Based on a Big Panel Dataset of China's 259 Cities. *J. Clean. Prod.* **2020**, *258*, 120721.
7. Lu, S.; Liu, Q.; Xia, S.; Zhang, W. How Does Industrial Transition Drive Low-Carbon Transition? Evidence from China's Resource-Based Cities. *Environ. Dev. Sustain.* **2024**, *10*, 8.
8. de Leeuw, F.A.; Moussiopoulos, N.; Sahm, P.; Bartonova, A. Urban Air Quality in Larger Conurbations in the European Union. *Environ. Model. Softw.* **2001**, *16*, 399–414.
9. Zhao, F.; Sun, Y.; Zhang, J. Does Industrial Agglomeration and Environmental Pollution Have a Spatial Spillover Effect? Taking Panel Data of Resource-Based Cities in China as an Example. *Environ. Sci. Pollut. Res.* **2023**, *30*, 76829–76841.
10. Hosoe, M.; Naito, T. Trans-Boundary Pollution Transmission and Regional Agglomeration Effects. *Pap. Reg. Sci.* **2006**, *85*, 99–119.
11. Zeng, D.-Z.; Zhao, L. Pollution Havens and Industrial Agglomeration. *J. Environ. Econ. Manag.* **2009**, *58*, 141–153.
12. Ye, Y.; Ye, S.; Yu, H. Can Industrial Collaborative Agglomeration Reduce Haze Pollution? City-Level Empirical Evidence from China. *Int. J. Environ. Res. Public Health* **2021**, *18*, 1566.
13. Chen, Y.; Zhu, Z.; Cheng, S. Industrial agglomeration and haze pollution: Evidence from China. *Sci. Total Environ.* **2022**, *845*, 157392.
14. Zhao, H.; Cao, X.; Ma, T. A spatial econometric empirical research on the impact of industrial agglomeration on haze pollution in China. *Air Qual. Atmos. Health* **2020**, *13*, 1305–1312.
15. Wu, L.; Wan, X.; Jahanger, A.; Li, M.; Murshed, M.; Balsalobre-Lorente, D. Does the Digital Economy Reduce Air Pollution in China? A Perspective from Industrial Agglomeration. *Energy Rep.* **2023**, *9*, 3625–3641.
16. Ang, B.W.; Goh, T. Index Decomposition Analysis for Comparing Emission Scenarios: Applications and Challenges. *Energy Econ.* **2019**, *83*, 74–87.
17. Dwivedi, A.K.; Soni, A. Drivers and Critical Paths of Carbon Emissions in India, a Structural Path Decomposition Analysis. *Energy Sources Part B* **2022**, *17*, 2084185.
18. Wu, X.; Zhou, S.; Xu, G.; Liu, C.; Zhang, Y. Research on Carbon Emission Measurement and Low-Carbon Path of Regional Industry. *Environ. Sci. Pollut. Res.* **2022**, *29*, 90301–90317.
19. Li, J.; Zhou, Y.; Chen, H. Measurement, Influencing Factors and Prediction on Carbon Emission Performance of Countries Along the Belt and Road. *Clean Technol. Environ. Policy* **2023**, *26*, 821–838.
20. Zhang, W.; Zhou, G.; Song, Z.; Shi, X.; Ye, M.; Chen, X.; Xiang, Y.; Zheng, W.; Zhang, P. Calculation of Carbon Emissions and Study of The Emission Reduction Path of Conventional Public Transportation in Harbin City. *Sustainability* **2023**, *15*, 16025.
21. Khan, Z.; Zhu, S.; Yang, S. Environmental Regulations an Option, Asymmetry Effect of Environmental Regulations on Carbon Emissions Using Non-Linear Ardl. *Energy Source Part A* **2018**, *41*, 137–155.
22. Xiao, H.; Zhou, Y.; Zhang, N.; Wang, D.; Shan, Y.; Ren, J. CO₂ emission reduction potential in China from combined effects of structural adjustment of economy and efficiency improvement. *Resour. Conserv. Recycl.* **2021**, *174*, 105760.
23. Doda, B.; Gennaioli, C.; Gouldson, A.; Grover, D.; Sullivan, R. Are Corporate Carbon Management Practices Reducing Corporate Carbon Emissions? *Corp. Soc. Responsib. Environ. Manag.* **2015**, *23*, 257–270.
24. Konadu, R.; Ahinful, G.S.; Boakye, D.J.; Elbardan, H. Board Gender Diversity, Environmental Innovation and Corporate Carbon Emissions. *Technol. Forecast. Soc.* **2022**, *174*, 121279.

25. Li, J.; Xu, X. Can Esg Rating Reduce Corporate Carbon Emissions?—An Empirical Study from Chinese Listed Companies. *J. Clean. Prod.* **2024**, *434*, 140226.
26. Zhang, X.; Pan, Z.; Tang, D.; Deng, Z.; Boamah, V. Impact of Environmental Regulation and Industrial Agglomeration on Carbon Emissions in the Yangtze River Economic Belt. *Sustainability* **2023**, *15*, 8308.
27. Zhao, J.; Dong, X.; Dong, K. How Does Producer Services' Agglomeration Promote Carbon Reduction?, The Case of China. *Econ. Model* **2021**, *104*, 105624.
28. Li, T.; Han, D.; Feng, S.; Liang, L. Can Industrial Co-Agglomeration between Producer Services and Manufacturing Reduce Carbon Intensity in China? *Sustainability* **2019**, *11*, 4024.
29. Mi, K.; Zhuang, R. Producer Services Agglomeration and Carbon Emission Reduction—An Empirical Test Based on Panel Data from China. *Sustainability* **2022**, *14*, 3618.
30. Li, H.; Liu, B. The effect of industrial agglomeration on China's carbon intensity: Evidence from a dynamic panel model and a mediation effect model. *Energy Rep.* **2022**, *8*, 96–103.
31. Tian, H.; Qin, J.; Cheng, C. Can industrial collaborative agglomeration improve carbon emission efficiency? Empirical evidence from China. *Environ. Sci. Pollut. Res. Int.* **2023**, *30*, 107899–107920.
32. Grossman, G.M.; Krueger, A.B. Economic growth and the environment. *Q. J. Econ.* **1994**, *110*, 353–377.
33. Ahmad, M.; Jabeen, G.; Khan, Z.; Anser, M.K.; Jabeen, G. Do Rural-Urban Migration and Industrial Agglomeration Mitigate The Environmental Degradation Across China's Regional Development Levels? *Sustain. Prod. Consum.* **2021**, *27*, 679–697.
34. Guo, W.; Atchike, D.W.; Ahmad, M.; Chen, Y.; Gu, S. Empirics on Linking Industrial Agglomeration, Energy Consumption, Residential Construction Sector Growth, and Environmental Sustainability. *Environ. Sci. Pollut. R.* **2023**, *30*, 66386–66399.
35. Brian, R.C.; Taylor, M.S. North-South Trade and the Global Environment. *Am. Q. J. Econ.* **1994**, *109*, 755–787.
36. Zhu, Y.; Xia, Y. Industrial Agglomeration and Environmental Pollution, Evidence from China Under New Urbanization. *Energy Environ.* **2018**, *30*, 1010–1026.
37. Hai-Shu, Q.; Wen-Yan, H.U.; Wei-Ya, Z. Specialized, Diversified Industrial Agglomeration and Energy Efficiency — An Empirical Study Based on Chinese Provincial Manufacturing Panel Data. *Econ. Surv.* **2015**, *32*, 85–90.
38. Panne, G.V.D. Agglomeration externalities: Marshall versus Jacobs. *J. Evol. Econ.* **2004**, *14*, 593–604.
39. Andreoni, J.; Levinson, A. The Simple Analytics of the Environmental Kuznets Curve. *J. Public Econ.* **2001**, *80*, 269–286.
40. Hou, J.; Teo, T.S.H.; Zhou, F.; Lim, M.K.; Chen, H. Does Industrial Green Transformation Successfully Facilitate a Decrease In Carbon Intensity in China? An Environmental Regulation Perspective. *J. Clean. Prod.* **2018**, *184*, 1060–1071.
41. Dai, P.; Lin, Y. Should There be Industrial Agglomeration in Sustainable Cities? A Perspective Based on Haze Pollution. *Sustainability* **2021**, *13*, 6609.
42. Liu, X.; Zhang, X. Industrial agglomeration, technological innovation and carbon productivity: Evidence from China. *Resour. Conserv. Recycl.* **2021**, *166*, 105330.
43. Acemoglu, D.; Gancia, G.A.; Zilibotti, F. Offshoring and Directed Technical Change. *Am. Econ. J. Macroecon.* **2015**, *7*, 84–122.
44. Wu, M.; Huang, W. Agglomeration and Green Technology Innovation Efficiency of Industrial Enterprises—Based on Spatial Statistical Analysis. *Arch. Environ. Prot.* **2022**, *48*, 3–14.
45. Jacobs, J. *The Economy of Cities*; Penguin Random House: New York, NY, USA, 1969.
46. Porter, M. *The Competitive Advantage of Nations*; The Free Press: Los Angeles, CA, USA, 1990.
47. Xu, D.; Yu, B. High-Tech Industry Agglomeration and Urban Innovation in the Yangtze River Delta from the Perspective of Spatial Spillover—Mediation Effect of Industrial Structure Optimization and Upgrading and Spatio-Temporal Heterogeneity Analysis. *Res. Dev. Manag.* **2023**, *35*, 15–29.
48. Ren, X.; Li, W.; Li, Y. Climate risk, digital transformation and corporate green innovation efficiency: Evidence from China. *Technol. Forecast. Soc.* **2024**, *209*, 123777.
49. Ai, X.; Zhang, H.; Guo, K.; Shi, F. Does Regional Innovation Environment Have an Impact on the Gathering of Technological Talent? An Empirical Study Based on 31 Provinces in China. *Sustainability* **2022**, *14*, 15934.
50. Krugman, P. Increasing returns and economic geography. *J. Political Econ.* **1991**, *99*, 483–499.
51. Xue, Q.; Bai, C.; Xiao, W. Fintech and corporate green technology innovation: Impacts and mechanisms. *Manag. Decis. Econ.* **2022**, *43*, 3898–3914.
52. Yang, S.; Ke, H.; Ye, Y.; Fan, F. Agglomeration and flow of innovation elements and the impact on regional innovation efficiency. *Int. J. Technol. Manag.* **2023**, *92*, 229–254.
53. Cabrer-Borras, B.; Serrano-Domingo, G. Innovation and R&D Spillover Effects in Spanish Regions, A Spatial Approach. *Res. Policy* **2007**, *36*, 13570–13571.
54. Liu, T.; Li, Z.; Zhang, C.; Xia, Q. How Comprehensive Innovation Reform Pilot Improve Urban Green Innovation Efficiency?—Evidence from China. *Sustainability* **2022**, *14*, 4550.
55. Cao, X.; Yu, J. Regional Innovation Efficiency in China from the Green Low-carbon Perspective. *China Popul. Environ.* **2015**, *25*, 10–19.
56. Huang, Y.; Wang, Y. How does high-speed railway affect green innovation efficiency? A perspective of innovation factor mobility. *J. Clean. Prod.* **2020**, *265*, 121623.
57. Tian, P.; Lin, B. Regional technology gap in energy utilization in China's light industry sector: Non-parametric meta-frontier and sequential DEA methods. *J. Clean. Prod.* **2018**, *178*, 880–889.

58. Huang, J.; Xia, J.; Yu, Y.; Zhang, N. Composite eco-efficiency indicators for China based on data envelopment analysis. *Ecol. Indic.* **2018**, *85*, 674–697.
59. Lin, Q.; Wang, M. Dynamic analysis of carbon dioxide emissions in China's petroleum refining and coking industry. *Sci. Total Environ.* **2019**, *671*, 937–947.
60. Xu, X.; Yang, G.; Tan, Y.; Zhuang, Q.; Tang, X.; Zhao, K.; Wang, S. Factors influencing industrial carbon emissions and strategies for carbon mitigation in the Yangtze River Delta of China. *J. Clean. Prod.* **2017**, *142*, 3607–3616.
61. Yang, W.; Wang, W.; Ouyang, S. The Influencing Factors and Spatial Spillover Effects of CO₂ Emissions from Transportation in China. *Sci. Total Environ.* **2019**, *696*, 133900.
62. Yan, Y.; Qi, S. Foreign Direct Investment and Air Pollution in China. *Stat. Res.* **2017**, *34*, 13.
63. Cong, J.; Liu, X.; Zhao, X. The Boundary Definition and Measurement Method of Urban Carbon Emission Accounting. *Chin. J. Popul. Resour. Environ.* **2014**, *24*, 8.
64. Yang, R. Industrial agglomeration and regional wage gap: An empirical study based on 269 Chinese cities. *J. Manag. World* **2013**, *8*, 41–52.
65. Yang, R.; Wei, Q. Research on the Influence of Business Environment on Urban Innovation Ability. *World Surv. Res.* **2021**, *10*, 9.
66. Jiang, S.; Shao, Y. Whether Industrial Agglomeration Leads to "Pollution Paradise": Based on the Data Analysis of 239 Prefecture-level Cities in China. *Ind. Econ. Rev.* **2020**, *4*, 109–118.
67. Yuan, H.; Liu, J.; Li, X.; Zhong, S. The impact of industrial collaborative agglomeration on total factor carbon emission efficiency in China. *Sci. Rep.* **2023**, *13*, 12347.
68. Chen, D.; Wang, Y. Influence mechanism of industrial agglomeration on carbon emission intensity—a perspective on borrowing performance. *Environ. Sci. Pollut. Res.* **2024**, *31*, 21737–21751.
69. Wu, X.; Zhu, M.; Pan, A.; Wang, X. Industrial agglomeration, FDI, and carbon emissions: New evidence from China's service industry. *Environ. Sci. Pollut. Res. Int.* **2024**, *31*, 4946–4969.

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