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Effects and Spatial Spillover of Manufacturing Agglomeration on Carbon Emissions in the Yellow River Basin, China

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Abstract: Manufacturing agglomeration is an important manifestation for cities to enhance their competitiveness, and the resource and environmental effects caused by agglomeration have become a hot topic. Based on the relevant data of prefecture-level cities in the Yellow River Basin from 2006 to 2019, this study used a Markov transition matrix to study the characteristics of carbon emission transfer and constructed an SDM model to analyze the effect of manufacturing agglomeration on carbon emissions and spatial spillover; the study drew the following conclusions: carbon emissions and the concentrations of manufacturing industries in the Yellow River Basin are on the rise, with carbon emissions showing a distribution pattern of "downstream > midstream > upstream". Manufacturing agglomeration has a significant positive influence on carbon emissions, reflecting the necessity for the green transformation of manufacturing agglomeration. Manufacturing agglomeration has a spatial spillover effect on carbon emissions. The direct effect is positive, and the indirect effect is negative. The polarization effect caused by agglomeration weakens the development degree of neighboring areas, which may reflect the technological spillover effect of manufacturing agglomeration on neighboring areas. Manufacturing agglomeration has regional heterogeneity in carbon emissions. Compared with the middle and lower reaches of the Yellow River Basin, the effect is more obvious in the upper reaches. The study proposes countermeasures in terms of optimizing the spatial pattern of the manufacturing industry and other aspects to provide references for promoting the transformation development of the manufacturing industry in the Yellow River Basin.

Keywords: manufacturing agglomeration; carbon emission; influential effect; spatial spillover; Yellow River basin

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1. Introduction

In recent years, global warming has attracted a lot of attention from many scholars. Carbon emissions from the massive consumption of fossil energy are considered to be a major cause of global warming [1]. Statistical Review of World Energy (71st edition), which was published by BP, shows that global energy consumption grew by 5.8% in 2021 due to accelerating economic activity. Therefore, a global consensus has been reached regarding vigorously promoting clean energy, improving energy efficiency, and reducing carbon emissions [2]. As a major emitter of carbon, China has fulfilled its obligations under the Paris Agreement and assumed its responsibilities as a major country. It has set a clearly defined goal, which is to reach its carbon peak in 2030 and carbon neutrality in 2060 [3]. As a significant ecological security barrier and economic development region [4], the low-carbon economic development of the Yellow River Basin is of vital importance to the achievement of China's dual carbon goal. The low development level, high proportion of high energy-consuming industries and unreasonable spatial layout constrain high-quality regional development [5]. The Yellow River Basin consumed 35.1% of the country's fossil energy in 2019 and produced 40.5% of the country's total carbon emissions. As an important energy base and industrial agglomeration area in China, it has a good manufacturing foundation and a well-developed system. The manufacturing industry occupies a dominant position in driving the regional development of basin, but the arbitrary structure of the manufacturing industry, insufficient innovation and R&D capabilities, and insufficient attention to technology introduction and transformation have constrained the low carbon development of the manufacturing industry [6]. Relevant studies suggest that manufacturing agglomeration characterized by technological innovation can promote the collaborative innovation of enterprises, strengthen resource utilization, and thus reduce carbon emissions. However, resource and energy endowments attract the spatial agglomeration of polluting industries, with no technological progress, knowledge spillover or optimization of resource allocation, which may intensify the competition for resources and factors in the agglomeration area and expand energy consumption to some extent. Therefore, it is important to study the effect of manufacturing agglomeration on carbon emissions in the Yellow River Basin to clarify the connection between manufacturing agglomeration and carbon emissions, and to promote the low-carbon transformation of the manufacturing industry.

The carbon dioxide content generated by energy consumption is the highest in greenhouse gas emissions, so carbon dioxide emissions are used as an index to measure greenhouse gas emissions and are referred to as carbon emissions. In addition to the total carbon emissions in the standard sense, for convenience, indicators such as carbon productivity and carbon emission intensity are also introduced [7–9]. Carbon emission measurements are calculated mainly by IPCC methods, input–output methods, MEIC models, etc. Among them, the IPCC method is widely used [10–13]. Many scholars have calculated the carbon emissions of different industries and sectors, such as industry, agriculture, tourism, and transportation. Studies on carbon emissions from land use [14], carbon emissions from energy consumption [15], and embodied carbon emissions from trade [16] have also gradually increased. Regarding the influencing factors of carbon emissions, related research focuses on urbanization [17], technological innovation [18], energy consumption scale [19], and industrial agglomeration [20], these studies use the LMDI model [21], spatial econometric model [22] and threshold effect to conduct in-depth research. According to IPCC (2019) data, China's carbon emissions from manufacturing accounted for 53.27% of the country's total carbon emissions in 2017. Manufacturing agglomeration is an important factor affecting carbon emissions. There are three main views on the relationship.

The first view is that manufacturing agglomeration will increase carbon emissions. This phenomenon generally appears in the early stage of manufacturing agglomeration. On the one hand, competing regions blindly pursue economic development and may lower environmental standards to attract industrial agglomeration [23]. Hence, the technical level of enterprises is not high, the production efficiency and energy utilization efficiency are low, and the massive expansion of production capacity is accompanied by severe pollution. On the other hand, agglomeration causes a shortage of land, labor, energy and other resources, illogical resource allocation, and vicious competition between enterprises. The negative externality effect of industrial agglomeration begins to become prominent, and the industry is characterized by "low efficiency and high energy consumption", resulting in a "crowding effect" [24], thus increasing carbon emissions. At the same time, in most manufacturing agglomeration areas, the centralized treatment of pollutants has not been realized, and the rate of pollutant treatment is low, further aggravating pollution [25].

The second view is that manufacturing agglomeration will reduce carbon emissions. This phenomenon generally appears in the later period of manufacturing agglomeration. On the one hand, manufacturing agglomeration can improve regional labor productivity and increase residents' income and fiscal revenue. Residents have a higher demand for a better environment, forcing the government to adopt stricter environmental policies to protect the environment [26,27]. Strict environmental regulations will bring "innovation compensation" to companies, further encouraging them to develop clean technologies. On the other hand, through the mechanism of sharing, matching, and learning, agglomeration promotes technological innovation, improves labor productivity, and strengthens the exchange and interaction of knowledge, technology, and capital among enterprises [28,29], resulting in an agglomeration spillover effect. In addition, the agglomeration of upstream and downstream industries in a geographical space facilitates the centralized production of products and the centralized treatment of pollutants [30] and achieves improvement of energy infrastructure, thus reducing carbon emissions [31].

The third view is that there is an upside-down U-shaped relation between manufacturing agglomeration and carbon emissions [32]. As the degree of manufacturing agglomeration increases, carbon emissions first increase and then decrease. In the early stage of manufacturing agglomeration, the structure of industry tends to be "pollution intensive," and carbon emissions increase with the expansion of the production scale of enterprises. In the middle and later stages of manufacturing agglomeration, the industrial structure is gradually optimized, and energy consumption decreases in the region. Overall, the effect of manufacturing agglomeration on carbon emissions is not a single linear relationship but results from the combined effect of the agglomeration effect and crowding effect [33]. As the level of manufacturing agglomeration increases, the positive effects, such as knowledge and technology spillover and cooperative competition brought by agglomeration, gradually outweigh the negative effects, such as congestion effect and energy consumption caused by excessive competition, and carbon emissions are reduced; otherwise, carbon emissions will be increased. There are also regional differences in the relationship between manufacturing agglomeration and carbon emissions, but they do not show a certain regularity. The main reason is that there are many factors affecting the relationship between manufacturing agglomeration and carbon emission, such as city size, economic development level, industrial structure, etc., all of which directly or indirectly affect the relationship between the two, making it difficult to sort out and summarize a general rule. The specialization of manufacturing agglomeration is significant in small cities, while the diversification of manufacturing agglomeration is more significant in large and medium-sized cities [34]. In developed countries such as Japan and the United States [35,36], manufacturing can form industrial clusters with other industries, promote information sharing and technological innovation, and reduce carbon emissions. The economic foundation of Western China is weak, the technological innovation ability is poor, the positive externalities generated by agglomeration are small, and the crowding effect is obvious. On the other hand, the Yangtze River Delta region of China has a solid economic foundation, a large number of scientific research talents, strong positive externalities brought by agglomeration, and less carbon emissions.

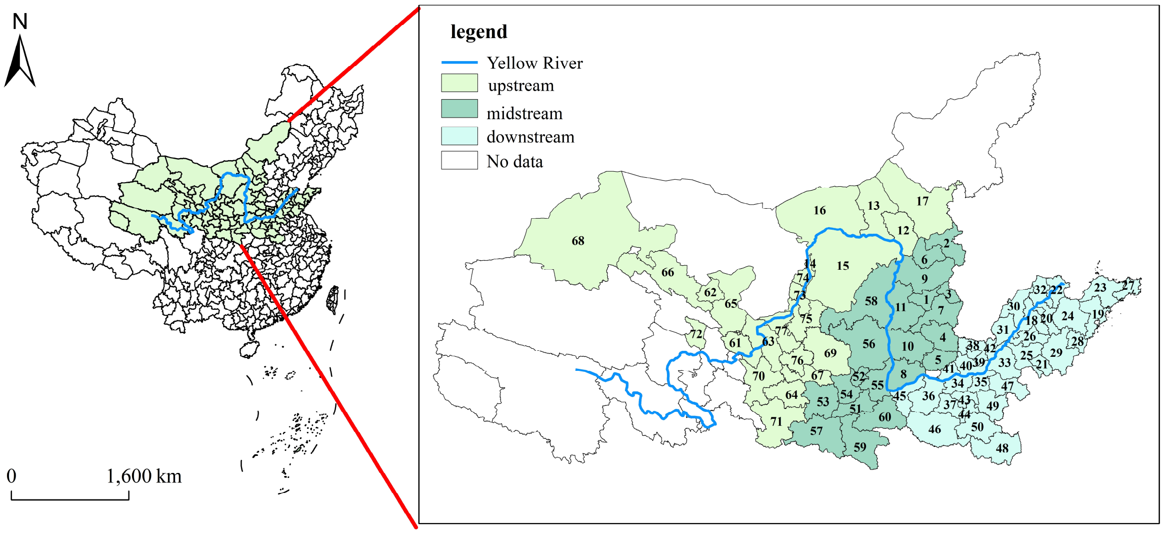
In general, the research on manufacturing agglomeration and carbon emissions in the relevant literature at home and abroad has made progress, but there are still various debates on the connection between manufacturing agglomeration and carbon emissions, and the conclusions vary by region and time scale. At the same time, there are relatively few studies on the effect of manufacturing agglomeration on carbon emissions in the Yellow River Basin. The literature that covers regional heterogeneity analysis is also relatively scarce. In this paper, the Markov transition matrix was used to study the transfer characteristics of carbon emission types, and the SDM model was constructed to empirically analyze the effect of manufacturing agglomeration on carbon emission and the spatial spillover effect and to study the regional heterogeneity of manufacturing agglomeration on carbon emission. This paper intends to make contributions from three aspects: (1) It considers regional differences in carbon emissions from the perspective of prefecture-level cities and enriches the research framework of the carbon emissions of prefecture-level cities. (2) We further elucidate the spatial spillover effect and regional heterogeneity of manufacturing agglomeration on carbon emissions in the Yellow River Basin. (3) The Markov transition matrix was used to analyze the transfer rules of carbon emission types in different regions of the Yellow River Basin, providing countermeasures for carbon emission reduction.

The remaining paper is organized as follows: the second section is the data and methods, the third section is the empirical analysis, the fourth section is the discussion, and the fifth section is the conclusion and countermeasures.

2. Materials and Methods

2.1. Study Area

According to the constructed index system, 77 prefecture-level cities in the Yellow River Basin are taken as research samples (Figure 1). Considering that Sichuan belongs to the Yangtze River Economic Belt, Hulunbuir, Chifeng, Tongliao and the eastern 4 League cities of Inner Mongolia of Hinggan League belong to the northeast, the study area of this paper is determined to be eight provincial administrative regions except Sichuan. The upstream region are Ningxia, Qinghai, Inner Mongolia and Gansu, the midstream region are Shaanxi and Shanxi, and the downstream region are Henan and Shandong.



(Upstream:77 Zhongwei, 76 Guyuan,75 Wuzhong,74 Shizuishan, 73 Yinchuan, 72 Xining, 71 Longnan, 70 Dingxi,69 Qingyang,68 Jiuquan, 67 Pingliang,66 Zhangye, 65 Wu wei,64 Tianshui,63 Baiyin,62 Jinchang,61 Lanzhou,17 Wulanchabu,16 Bayannaoer,15 Eerduosi,14 Wuhai, 13 Baotou,12 Huhehaote.
Midstream: 59 Ankang, 58 Yulin, 57 Hanzhong, 56 Yanan, 55 Weinan, 54 Xianyang, 53 Baoji, 52 Tongzhou, 51 Xi'an, 11 Lvliang,10 linfen, 9 Xinzhou,8 Yuncheng,7 Jinzhong,6 Shuozhou,5 Jincheng,4 Changzhi,3 Yangquan,2 Datong,1 Taiyuan.
Downstream:50 Zhumadian,49 Zhoukou, 48 Xinyang,47 Shangqiu,46 Nanyang,45 Sanmenxia,44 Luohe,43 Xuchang,42 Puyang,41 Jiaozuo, 40 Xinxiang, 39 Hebi, 38 Anyang, 37 Pingdingshan,36 Luoyang,35 Kaifeng,34 Zhengzhou, 33 Heze, 32 Binzhou, 31 Liaocheng,30 Dezhou, 29 Linyi,28 Rizhao,27 Weihai,26 Taian,25 Jining,24 Weifang,23 Yantai,22 Dongying,21 Zaozhuang,20 Zibo,19 Qingdao,18 Jinan.)

Figure 1. The extent of the study area.

2.2. Research Methods

2.2.1. Markov Transition Matrix

The carbon emission transfer pattern of prefecture-level cities in the Yellow River basin is studied by the Markov transfer matrix [37], which is calculated as follows:

$$prob_{uv}^{t,t+d} = \frac{\sum_{t=T_0}^{T-d} n_{uv}^{t,t+d}}{\sum_{t=T_0}^{T-d} n_{u}^{t,t+d}} \quad (u = 1,\ 2,\ \ldots, k;\ v = 1,\ 2,\ \ldots,\ k;\ t = T_0,\ \ldots,\ T-d) \tag{1}$$

where k represents the number of grades of carbon emission types. prob is the transfer probability of carbon emission type. According to the natural break point method, this paper divides carbon emissions into four types: I, II, III and IV. Therefore, k is equal to 4; d represents the transfer period of cities between different levels; n_{uv} denotes the number of cities shifting from echelon u of year t to echelon v of year $t + d$; and n_u denotes the number of cities belonging to the U-echelon in year t.

2.2.2. Spatial Autocorrelation

Moran's I index reflects the correlation degree of attribute values in the whole region. The index was used to analyze the spatial aggregation of carbon emissions in the Yellow River Basin. The calculation formula is as follows:

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

where n is the number of samples; $\overline{x}$ is the sample mean; w_{ij} is the element in the spatial weight matrix, and the spatial weight used in this paper is the Queen spatial weight matrix.

2.2.3. Spatial Panel Durbin Model

Compared with the traditional OLS regression, the spatial panel model can consider the influence of spatial interaction factors and effectively solve the possible model estimation bias [36]. Therefore, to further study the spatial dependence and spillover effect of manufacturing agglomeration on carbon emissions, this paper adopts the spatial Durbin model [26]:

$$\ln CE_{it} = \alpha_i + \rho\sum_{i=1}^{n} W_{ij}\ln CE_{it} + \varphi X_{it} + \theta\sum_{i=1}^{n} W_{ij}X_{it} + u_i + \delta_i + \varepsilon_{it} \tag{3}$$

where lnCE_{it} denotes the carbon emissions, i and j both represent urban individuals, n is the number of cities, α_i is the constant term, ρ is the spatial regression coefficient, X is the independent variable, φ is the regression coefficient of the independent variable, u_i and δ_i are city fixed effect and time fixed effect, θ is the coefficient of its spatial lag term, ε_{it} is the random disturbance term, W_{ij} represents the weight matrix, and $W_{ij}X_{it}$ is its spatial lag term.

2.3. Data Sources

Due to the lack of data for some prefectures resulting from administrative division adjustment and missing data, this paper selects 77 prefectures as the study area after the exclusion process. The data are mainly from the 2006 to 2019 China Statistical Yearbook and the statistical yearbooks of each city (district), etc. For missing data, the linear interpolation method is used to fill in the data gaps [38].

2.3.1. Explained Variables: Carbon Emission (CE)

The explained variable is carbon emissions. Eight energy sources, including raw coal, coke, crude oil, gasoline, kerosene, diesel, fuel oil, and natural gas, are selected to calculate the total carbon emissions according to the IPCC (2006) [38]:

$$CE_i = \sum_{i=1}^{8}(CO_2)_i = \sum_{i=1}^{8} E_i \times SCC_i \times CEF_i \tag{4}$$

CE_i represents total carbon emissions; i represents the type of fossil energy; E_i, SCC_i, and CEF_i represent the consumption of Class i fossil energy, the conversion coal coefficient of fossil energy, and the carbon emission coefficient, respectively.

2.3.2. Core Explanatory Variables: Location Quotient (LQ)

According to the relevant research literature at home and abroad, Location quotient, Herfindahl Hirschmann index (HHI), and EG index are commonly used to measure the degree of industrial agglomeration. Among them, *LQ* is widely used, as it can better reflect the spatial distribution of geographical factors [39]. The measurement method is as follows:

$$LQ = \left[\left(\frac{Ln_{itj}}{\sum_{j=1}^{n} Ln_{itj}} \right) / \left(\frac{\sum_{i=1}^{m} Ln_{itj}}{\sum_{j=1}^{n} \sum_{i=1}^{m} Ln_{itj}} \right) \right] \quad (5)$$

Ln is the number of employees in industry *j* in year t of city *i*; *n* is the number of industries; and m is the number of cities.

2.3.3. Control Variables

According to the previous literature, the carbon emission level of the region is affected not only by industrial energy consumption, but also by the level of economic development (PIN), population density (PD), industrial structure (IS2), land urbanization (URB), and government macroeconomic regulation (GR) [40–42]. The process of economic development is accompanied by energy consumption. The environmental Kuznetz curve suggests an inverted U-shaped relationship between economic development and carbon emissions [43,44]. The increase in population density will aggravate the energy consumption of production and day-to-day activities and increase carbon emissions. As a highly energy-consuming and polluting industry, the secondary industry has a great impact on carbon emissions [45]. Government macroeconomic regulation and the level of urbanization have an important impact on carbon emissions [46]. URB was measured by the proportion of urban construction land in the urban areas. IS2 was measured by the ratio of secondary industry output value to GDP; PIN was measured by regional GDP per capita. PD was measured by the number of people per square kilometer; GR was measured as the ratio of fiscal expenditure to GDP. The description of the relevant variables in the regression is shown in Table 1.

Table 1. Variable declaration.

Variables	Obs	Mean	SD	Min	Max
lnCE	1077	5.967	1.165	2.117	8.4
lnLQ	1077	−0.313	0.691	−3.713	0.969
lnPIN	1077	10.403	0.74	7.926	12.456
lnPD	1077	5.578	1.088	1.547	7.273
lnIS2	1077	−0.707	0.272	−1.997	0.112
lnGR	1077	−1.735	0.632	−3.155	1.354
lnURB	1077	−3.072	1.241	−8.517	−0.064

Note: Obs, SD, Min, and Max. represents observations, standard deviation, minimum, and maximum.

3. Results

3.1. Spatial and Temporal Distribution of Carbon Emissions and Manufacturing Agglomeration

3.1.1. Spatial Differentiation of Carbon Emissions and Manufacturing Agglomeration Levels

This study selects the cross-sectional data of four time points in 2006, 2010, 2014, and 2019, divides the degree of manufacturing agglomeration into four levels, and explores the spatial distribution characteristics of manufacturing agglomeration. Overall, the concentration level of the manufacturing industry fluctuates and increases, and the concentration level of the manufacturing industry in the lower reaches is better than that in the middle and upper reaches (Figure 2). The lower reaches have the highest concentration level in the manufacturing industry, and the mean LQ of the lower reaches in 2019 is 1.21, among which Weihai, Binzhou, and Luohe are 2.63, 2.19, and 2.34, respectively. The superior geographical location and factor endowment of the downstream region are more likely to attract industrial and population agglomeration. In addition, there are many large cities in the downstream region, whose population and scale advantages are conducive to the further extension of the industrial chain, leading to industrial agglomeration. The mean LQ of the middle reaches is 0.64, and those of Baoji City, Xi'an City, and Yuncheng City are 1.64, 1.05, and 1.01, respectively. The average LQ of the upstream region is 0.67, and those of Jinchang, Baotou, and Shizuishan are 1.90, 1.24, and 1.18, respectively. The upstream and midstream regions are inland, and thus are less open to the outside world and less able to introduce overseas capital and technology. In addition, the road transportation infrastructure in the middle and upper reaches of the region is weak, the scale of the manufacturing industry is low, and the small scale of industry inhibits the formation of an adequate labor market and complete upstream and downstream relationships, which also inhibits manufacturing industry agglomeration to a certain extent.

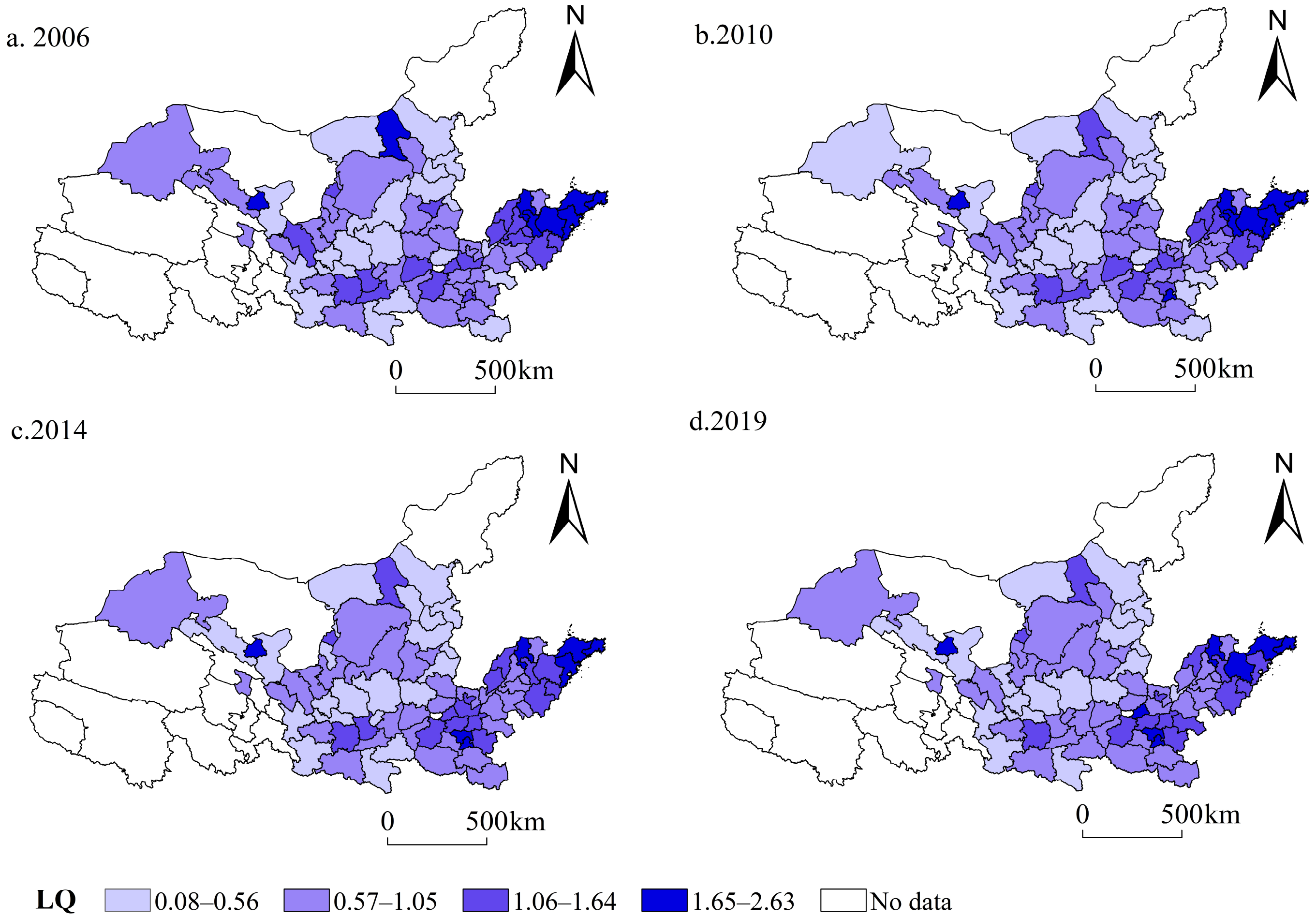


Figure 2. Spatial distribution of manufacturing agglomeration degree in prefecture-level cities along the Yellow River Basin from 2006 to 2019 (**a**–**d**).

Cross-section data were selected from four time points in 2006, 2010, 2014, and 2019. Using ArcGIS, carbon emissions in the Yellow River Basin were divided into four levels: "type I" (8.38~456.70 ten thousand tons), "type II" (456.71~1113.90 ten thousand tons), "type III" (1113.91~1945.20 ten thousand tons), and "type IV" (1945.21~4445.30 ten thousand tons), with carbon emissions increasing step by step, to explore the spatial distribution characteristics and rules of carbon emissions in the Yellow River Basin (Figure 3). The spatial variation in carbon emissions in the Yellow River Basin is obvious, and cities with higher and lower carbon emissions have obvious spatial agglomeration characteristics. Among them, Qingdao, Weifang, Jinan, Baotou, Hohhot, Yulin, Xi'an, and other developed areas have higher carbon emissions, while Jiuquan, Zhangye, Bayannur, Ordos, and other relatively less developed areas have lower carbon emissions. In 2019, Jinan, Xi'an, and Weifang had the highest carbon emissions of 4445.30, 4045.59, and 36.814,800 tons, respectively, while Zhoukou, Longnan, and Dingxi had the lowest carbon emissions of 113.68, 51.32, and 492,400 tons, respectively.

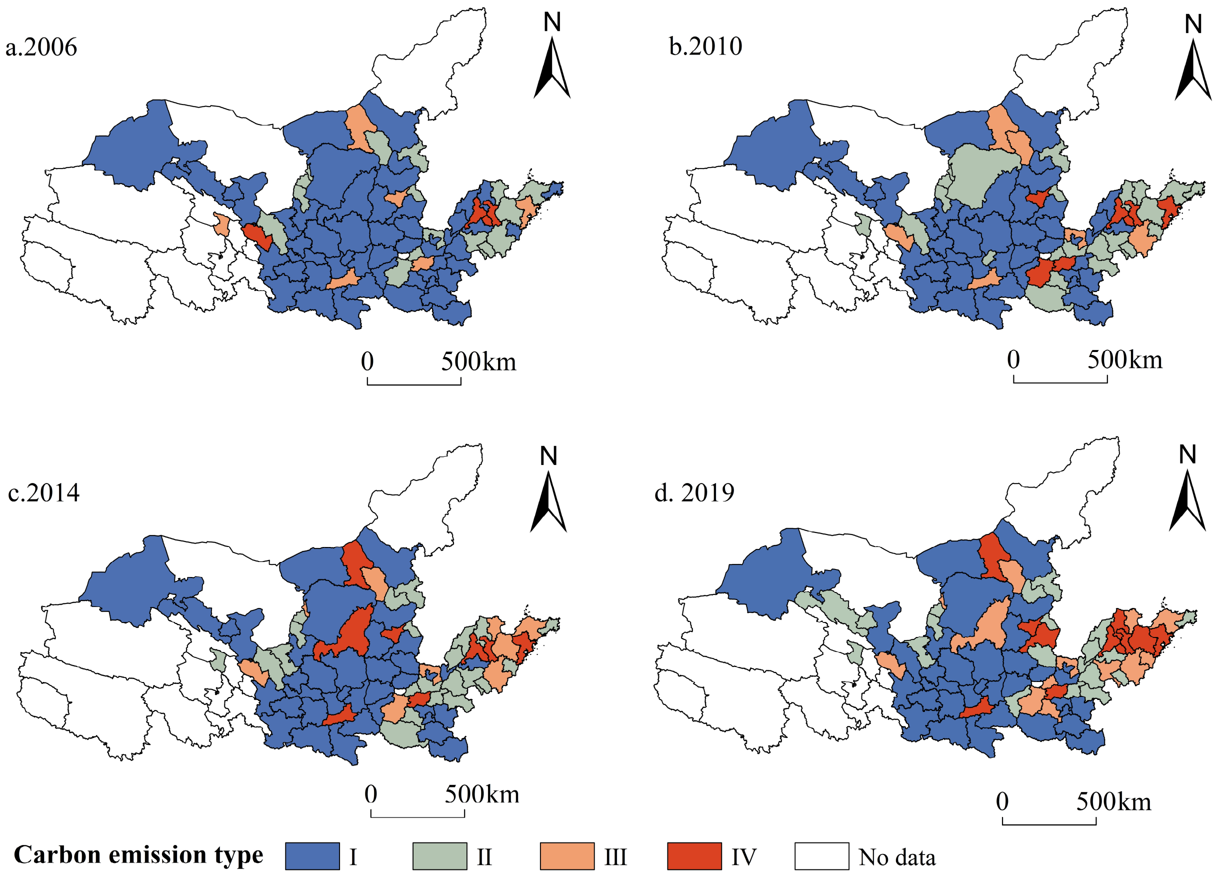


Figure 3. Spatial distribution of carbon emissions in cities along the Yellow River Basin from 2006 to 2019 (**a**–**d**).

Spatial differences in carbon emissions were further analyzed from the upstream, midstream, and downstream of the basin. In 2019, the average carbon emissions in the lower reaches were 12.8608 million tons, the average carbon emissions in the middle reaches were 8.2721 million tons, and the average carbon emissions in the upper reaches were 6.8087 million tons. The distribution pattern of carbon emissions was "downstream > midstream > upstream", and the spatial polarization effect was very obvious. From 2006 to 2019, the overall carbon emissions of the Yellow River Basin showed an increasing trend, and the lower reaches were dominated by type II to type IV, while the upper reaches were dominated by type I, but the carbon emissions also increased slightly. Shandong Province and Henan Province are the most intensive and developed regions in the Yellow River Basin with heavy industrial structure. In the process of rapid economic development, a large amount of energy consumption and increased carbon emissions are inevitable. The downstream area has a dense population, a broad market, a large demand for manufacturing products, a relatively large manufacturing scale, and relatively high carbon emissions.

3.1.2. Markov Transition Matrix

According to the above classification principle of carbon emissions, carbon emissions can be divided into four types: I, II, III, and IV. Upward transfer refers to the transformation from low carbon emissions to high carbon emissions, while downward transfer is the opposite. The Markov transition matrix of carbon emission types in the Yellow River Basin from 2006 to 2019 was calculated (Table 2).

Table 2. Markov transition matrix.

Type	I	II	III	IV
I	90.18%	8.00%	1.27%	0.55%
II	10.32%	80.16%	9.13%	0.40%
III	5.83%	7.50%	78.33%	8.33%
IV	3.80%	1.27%	3.80%	91.14%

(1) The probabilities on the diagonal in the matrix are much larger than those on the non-diagonal, indicating that the odds of constant carbon emission types in the Yellow River Basin are larger than the odds of shifts occurring. The main reason is that due to the original socio-economic and resource endowment conditions, the economic development model of the Yellow River Basin is characterized by path dependence, and the scale of carbon emissions exhibits the characteristics of path locking, showing the phenomenon of "the higher is always higher and the lower is always lower". (2) The probabilities of I → I, II → II, III → III, and IV → IV were 90.18%, 80.16%, 78.33%, and 91.14%, respectively. The probabilities of I → I and IV → IV were greater than those of II → II and III → III. The results show that there is a "club convergence" phenomenon of carbon emissions, and the probability of the intermediate type maintaining the original type is low. This may be related to the level of local economic development. Intermediate prefecture-level cities are mainly located in the lower reaches of the Yellow River Basin, with a relatively high level of economic development. Government, enterprises, and people pay more attention to the environment and invest more money, so it is easier to reduce carbon emissions. Therefore, the focus is on the optimal regulation of type II and III areas to promote the reduction in carbon emissions in the basin. (3) The probability of I → II is 8.00%; the probability of I → III is 1.27%; the probability of I → IV is 0.55%; the probability of II→III is 9.13%; and the probability of II→IV is 0.40%. The carbon emission type is transformed step by step, and the difficulty of cross-step transition is gradually increased. (4) The sum of the probability of downward and upward transfer of carbon emission types is 32.52% and 27.68%, respectively. The probability of downward shift is higher, indicating that the carbon emission situation in the Yellow River Basin is gradually improving, but the pressure of carbon emission reduction is still severe, and the concept of green and low-carbon development must continue to be implemented in the future.

3.1.3. Spatial Autocorrelation Analysis

Moran's *I* index of carbon emissions of prefecture-level cities in the Yellow River Basin was positive from 2006 to 2019 (Table 3) and passed the significance test of 1% and 5% in all years except 2014. The results indicate that there is a positive spatial association of carbon emissions, with high-high and low-low clustering. Generally, Moran's *I* index fluctuated in the range of 0.077–0.282 from 2006 to 2019, and Moran's *I* index showed a trend of first decreasing and then increasing. This indicates that the positive spatial correlation of carbon emissions in adjacent regions decreases first and then increases, and the positive spatial correlation of carbon emissions in 2018 is the strongest. This finding suggests the need to consider spatial factors when studying the effect of manufacturing agglomeration on carbon emissions.

3.2. Spatial Panel Model Selection and Regression Analysis

3.2.1. Model Selection

LM and LR are used to select the forms of spatial metrology models (Table 4). The LM test shows that both the spatial panel lag model and the spatial panel error model are suitable for analyzing the relationship between manufacturing agglomeration and carbon emissions. Therefore, the LR test is further adopted, and it rejects the spatial Durbin model (SDM) to degenerate into a spatial lag model (SAR) and spatial error model (SEM). Therefore, the spatial Durbin model is selected for estimation in this paper (Table 5).

Table 3. Moran's *I* index results.

Year	Moran's *I*	Z-Statistic
2006	0.185 ***	2.8170
2007	0.183 ***	2.7072
2008	0.170 **	2.5300
2009	0.158 **	2.2895
2010	0.161 **	2.5788
2011	0.161 **	2.4948
2012	0.133 **	1.9940
2013	0.137 **	1.9637
2014	0.077 *	1.0419
2015	0.183 **	2.6805
2016	0.255 ***	3.6676
2017	0.281 ***	3.9190
2018	0.282 ***	3.9133
2019	0.235 ***	3.2616

Note: *** $p < 0.01$; ** $p < 0.05$; and * $p < 0.1$.

Table 4. Model selection.

Spatial Autocorrelation Text	Statistic
LM-lag	14.535 ***
Robust LM-lag	21.171 ***
LM-Error	21.253 ***
Robust LM-Error	27.889 ***
LR-lag	51.33 ***
LR-Error	37.22 ***

Note: *** $p < 0.01$.

Table 5. Regression result.

Variable	(1)	(2)	(3)
	SAR	SEM	SDM
lnLQ	0.153 *** (3.43)	0.169 *** (3.66)	0.196 *** (4.16)
lnPIN	0.541 *** (10.38)	0.641 *** (14.35)	0.829 *** (10.09)
lnPD	0.390 *** (4.99)	0.408 *** (5.39)	0.621 *** (5.93)
lnIS2	−0.219 ** (−2.33)	−0.204 ** (−2.09)	−0.243 ** (−2.12)
lnGR	−0.135 *** (−3.73)	−0.110 ** (−2.33)	−0.016 (−0.27)
lnURB	−0.060 ** (−2.30)	−0.065 ** (−2.54)	−0.057 ** (−2.22)
W × lnLQ			−0.565 *** (−2.61)
W × lnPIN			−0.569 *** (−4.74)
ρ	0.137 (1.45)		0.346 *** (3.13)
N	1078	1078	1078
R^2	0.560	0.583	0.636

Note: *** $p < 0.01$; ** $p < 0.05$.

3.2.2. Spatial Model Estimation Results and Spatial Spillover Effect

From SAR to SDM, the sign and statistical significance of the core explanatory variables and other control variables did not change significantly, and only the size of the parameter estimates changed.

The effect of manufacturing agglomeration on carbon emissions is significantly positive. On the one hand, as an "energy" basin of China, the Yellow River Basin is rich in energy reserves such as coal, oil, and natural gas, and resource-based cities account for 51%. Industries with high energy consumption and high pollution account for a large proportion, and the industrial structure tends to be "pollution-intensive". The large-scale agglomeration of the manufacturing industry in the geographical space brings the expansion of population and production scale. The superposition of the industrial scale effect and energy intensity effect makes the output increase substantially, while carbon emissions, as an undesirable output, will also increase. On the other hand, due to the low level of overall manufacturing agglomeration, the labor pool effect, intermediate input sharing effect and knowledge, and technology spillover effect brought by manufacturing agglomeration are weak, the availability and matching degree of the labor force are low, the interaction of capital, technology, and knowledge among enterprises is minimal, and the "positive" agglomeration effect brought by agglomeration is small. This situation causes the manufacturing industry to demonstrate "low efficiency" and "high energy consumption", leading to more energy consumption and carbon emissions.

In terms of control variables, the level of economic development can increase carbon emissions to some extent. The majority of cities in the Yellow River Basin are relatively economically underdeveloped and are mainly experiencing extensive development. As the economic development level rises, energy consumption and carbon emissions also increase gradually. The impact of population density on carbon emissions is positive, and an increase in population density causes traffic congestion, more buildings, and increased energy consumption, thus increasing carbon emissions. The effect of industrial structure on carbon emissions is negative. With the adjustment of China's industrial structure, the optimization of the industrial geographical pattern, the transfer of industry from the East to the West, and the spillover of technology and knowledge, technological progress, and R&D innovation occurring, the green transformation of the industry is promoted, and carbon emissions are reduced to some extent. The effect of urbanization on carbon emissions is negative. With the accelerated urbanization process, residents' demand for a better environment increases, thus, promoting energy conservation and emission reduction in the basin at the social level. Government macroeconomic regulation has a negative but insignificant effect on carbon emissions. With the implementation of the dual carbon goals, local governments actively respond to the dual carbon goals, advocate green and low-carbon development, and carry out energy conservation and emission reduction activities. However, sometimes there is excessive government intervention in the process of economic activities, which cannot play the part of the market in resource allocation, and the effect of carbon emission reduction is not obvious.

Regarding the spatial spillover effect (Table 6), The impact of manufacturing agglomeration on local carbon emissions is positive and significant at the 1% level, and manufacturing agglomeration increases carbon emissions. However, manufacturing agglomeration has a negative effect on carbon emissions in neighboring areas, which is significant at the 5% level. Hence, manufacturing agglomeration reduces carbon emissions in neighboring areas. The spatial spillover effect can be represented by polarization effect and radiation effect. When the polarization effect dominates, the manufacturing agglomeration has a negative spatial spillover effect on the neighboring areas; when the diffusion effect dominates, the manufacturing agglomeration has a positive spatial spillover effect on the neighboring areas. The agglomeration of the manufacturing industry in the Yellow River Basin is in its early stage, and the polarization effect is greater than the diffusion effect. The agglomeration gravity brought by the agglomeration will attract factors and capital from the surrounding provinces to converge to the region, exacerbating the differences and imbalances in the spatial distribution of resources and factors. While expanding the scale of manufacturing in this region and increasing energy consumption, the development of manufacturing in neighboring regions is limited, reducing energy demand and carbon emissions in the region. On the other hand, although the radiation effect is weak, it will also spread knowledge and technology to neighboring areas to some extent [47]. Optimizing the industrial structure of the neighboring region, improves innovation ability, improves energy efficiency, and reduces the cost of enterprises. The combination of these two factors leads to the reduction in carbon emissions in the neighboring region.

Table 6. Decomposition of the spatial spillover effect.

Variable	Direct Effect		Indirect Effect		Total Effect	
	Coef	z	Coef	z	Coef	z
lnLQ	0.192 ***	(4.03)	−0.768 **	(−2.21)	−0.576 *	(−1.69)
lnPIN	0.823 ***	(10.47)	−0.425 ***	(−3.25)	0.397 ***	(4.06)
lnPD	0.620 ***	(6.34)	−1.524 **	(−2.33)	−0.904	(−1.48)
lnIS2	−0.251 **	(−2.23)	−1.259 ***	(−3.79)	−1.510 ***	(−4.88)
lnGR	−0.018	(−0.30)	−0.212 **	(−2.16)	−0.230 ***	(−2.95)
lnURB	−0.059 *	(−1.94)	0.814 **	(2.37)	0.764 **	(2.19)

Note: *** $p < 0.01$; ** $p < 0.05$; and * $p < 0.1$.

3.2.3. Robustness Test

In this paper, the robustness of the results is tested from three aspects. The lag period of the explained variable (carbon emissions) is selected as the instrumental variable, the per capita GDP of each city is used to establish the economic distance matrix, the economic geographical weight matrix is used to replace the geographical distance weight matrix, and the Herfindahl–Hirschmann index (HHI) is used to replace the LQ. Recalculated concentration levels for manufacturing are shown in Table 7. After the recalculation, no significant difference between the above three results and the conclusion of this paper is traced. The influence of manufacturing agglomeration on carbon emissions is significantly positive, therefore, the results of this paper are robust.

Table 7. Robustness test results.

Variable	(1)	(2)	(3)
	Lag Explained Variable	Change the Spatial Weight Matrix	Change the Core Explanatory Variable
lnLQ		0.151 *** (3.36)	
lnHHI			0.121 *** (2.77)
L.lnCE	0.927 *** (83.77)		
P	0.446 *** (4.76)	0.038 (0.63)	0.257 ** (2.13)
Control	Yes	Yes	Yes
Observations	1078	1078	1078

Note: *** $p < 0.01$; ** $p < 0.05$.

3.2.4. Heterogeneity Analysis

Economic development in the Yellow River Basin is uneven [48], and the concentration levels of manufacturing industries upstream, midstream, and downstream are quite different. The influence of upper, middle, and downstream manufacturing agglomeration on carbon emissions was studied and analyzed. The results of the upstream and midstream regions were basically consistent with the overall model, while there were differences in the downstream regions (Table 8). The effect of manufacturing agglomeration on carbon emissions in the middle and upper reaches is significantly positive. The manufacturing agglomeration in the downstream area has no significant impact on the carbon emissions of the local area but has a negative impact on the carbon emissions of the neighboring areas. The lower reaches mainly include Henan Province and Shandong Province. Compared to the upper and middle reaches, the superior geographical location of the lower reaches more easily forms industrial and population agglomerations. The geographical location of coastal areas is conducive to attracting overseas capital and advanced technology, improving the traditional development mode, optimizing the industrial structure of enterprises and making the allocation of resources more reasonable. Therefore, the degree of manufacturing agglomeration is relatively high, and it is in the transition stage from increasing carbon emissions to reducing carbon emissions. The low-carbon transformation of the manufacturing industries is an issue that must be considered in the future.

Table 8. Results of heterogeneity analysis.

Variable	Upstream		Midstream		Downstream	
	Direct	Indirect	Direct	Indirect	Direct	Indirect
lnLQ	0.302 ***	0.319	0.262 **	−0.338	0.070	−0.774 ***
	(3.47)	(0.89)	(2.54)	(−1.10)	(1.08)	(−2.63)
lnPIN	0.887 ***	−0.040	1.103 ***	−0.462 **	0.315 ***	0.302
	(6.29)	(−0.19)	(6.39)	(−2.18)	(2.83)	(1.47)
lnPD	0.556 ***	−0.757	1.064 ***	−2.527 ***	0.404 *	−1.138
	(4.62)	(−0.94)	(4.66)	(−3.01)	(1.79)	(−0.60)
LnIS2	−0.175	−0.481 *	1.064 ***	−1.071 **	−0.143	−0.463
	(−0.94)	(−1.68)	(4.66)	(−2.53)	(−0.71)	(−1.03)
lnGR	−0.052	−0.216	0.089	−0.434 ***	0.076	−0.152
	(−0.44)	(−1.23)	(0.78)	(−2.77)	(1.06)	(−1.50)
lnURB	−0.038	−0.064	−0.050	0.171	−0.181 ***	0.165
	(−0.84)	(−0.33)	(−0.93)	(0.61)	(−5.47)	(0.60)

Note: *** $p < 0.01$; ** $p < 0.05$; and * $p < 0.1$.

At the same time, Shandong Province and Henan Province also have spatial spillover effects on their neighboring regions. Labor, capital, technology, and other factors flow into the surrounding areas, promote the spillover effect of knowledge and technology through sharing, lead to matching and learning mechanisms, accelerate technical innovation of enterprises, promote the green transformation of industrial structure, constantly eliminate energy-intensive and inefficient industries, reduce energy consumption, and reduce carbon emissions in neighboring areas. The regression results show that the influence coefficient of manufacturing agglomeration on carbon emissions is the highest in the upstream region, followed by the middle reaches, and is lowest and insignificant in the downstream region. This may be related to the lower industrialization development stage in the upstream region, the relatively limited improvement degree of energy utilization and technical efficiency, and the relatively large marginal effect of manufacturing agglomeration on carbon emissions.

4. Discussion

Carbon reduction in manufacturing is an important path to achieving the dual carbon goal. The study of the impact of manufacturing agglomeration on carbon emissions can provide a basis for carbon emission reduction. By establishing the spatial Dubin model, we found that from the perspective of the whole Yellow River Basin, manufacturing agglomeration will increase the local carbon emissions, which is similar to the conclusion of Zhang et al. [49,50] but will reduce the carbon emissions of neighboring regions. This is mainly related to the stage of manufacturing agglomeration in the Yellow River Basin. The manufacturing agglomeration in the Yellow River Basin is in the early stage, and the labor reservoir effect and intermediate input sharing brought by agglomeration are weak, while the crowding effect is dominant, which will increase carbon emissions in the region [51]. The spatial spillover effect on neighboring areas is mainly negative, mainly because the polarization effect is greater than the radiation effect, attracting capital, talent, technology and other factors in neighboring areas, hindering the information exchange and knowledge spillover between enterprises in neighboring areas, and reducing carbon emissions (Figure 4).

In addition, we tried to study the relationship between manufacturing agglomeration and carbon emissions from different reaches of the Yellow River basin, which is also an innovation point of this paper. We found that the middle and upper reaches of the Yellow River Basin, like the whole basin, are still in the early stage of manufacturing agglomeration, but the lower reaches are in the transition stage of manufacturing agglomeration from the early stage to the late stage due to a relatively developed economy, and the spatial spillover effect on neighboring areas is mainly positive. The radiation effect is greater than the polarization effect; advanced technology and production processes spread to the surrounding areas, reduce the production cost of enterprises, increase the investment in research and development technology, promote the collaborative innovation and technological progress of enterprises in the neighboring areas, optimize and upgrade the industrial structure, and reduce the carbon emissions in the neighboring areas. The manufacturing industry in the Yellow River Basin faces great pressure of carbon emission reduction, so green transformation is very necessary. The manufacturing industry in the Yellow River Basin faces great pressure of carbon emission reduction, so green transformation is very necessary. In particular, the upstream region undertakes energy-intensive industries from the downstream region, which to some extent leads to the "pollution refuge" effect. Therefore, it is necessary to design the optimal agglomeration mode and build a modern manufacturing system according to the characteristics of the manufacturing industry [52].

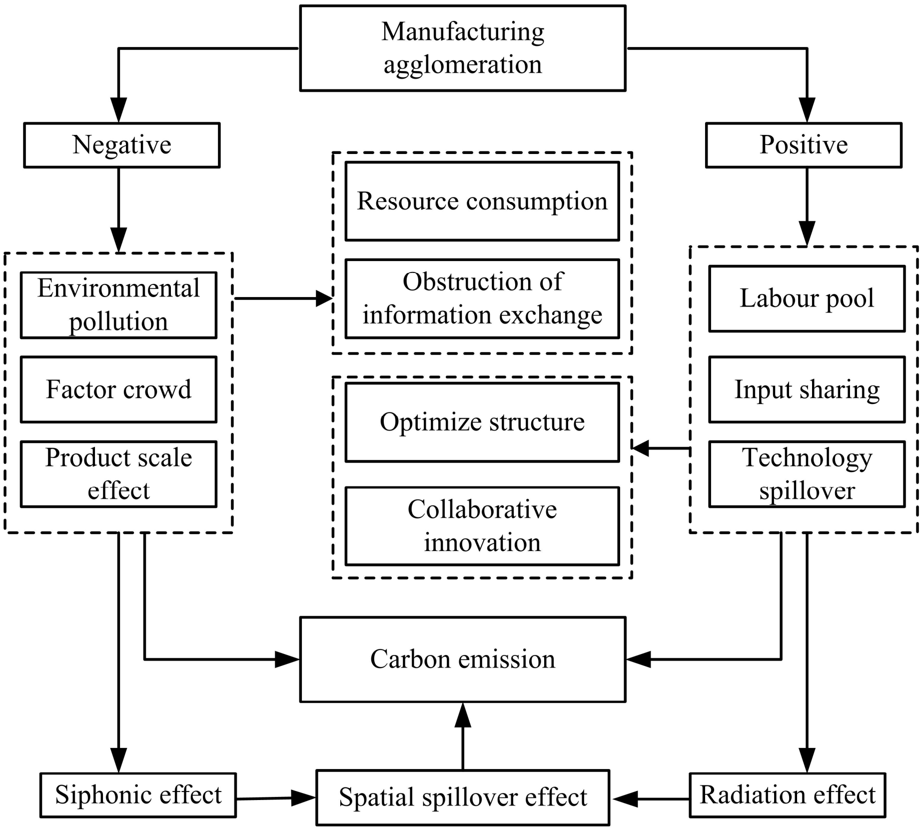


Figure 4. The influence mechanism of manufacturing agglomeration and carbon emissions.

Existing studies mostly focus on the relationship between industrial agglomeration and environmental pollution. For example, Fang et al. [28] believe that manufacturing agglomeration will reduce haze pollution in local and surrounding areas. This paper explores the relationship between manufacturing agglomeration and carbon emissions, further considers regional heterogeneity, and compares the similarities and differences between manufacturing agglomeration and carbon emissions in different river reaches of the basin, which is innovative to a certain extent. Due to limited data sources and research time, there are still some limitations. In the future, research on the impact and spillover effect of manufacturing agglomeration on carbon emissions at the county scale or in typical case areas can be further strengthened.

5. Conclusions and Policy Suggestions

5.1. Conclusions

Based on the panel data of the Yellow River Basin from 2006 to 2019, the spatial and temporal pattern characteristics of manufacturing agglomerations and carbon emissions were analyzed, and a panel SDM model was constructed to empirically test the effect and spatial spillover of manufacturing agglomeration on carbon emissions. The main conclusions are as follows:

(1) From 2006 to 2019, both the degree of manufacturing agglomeration and carbon emissions showed an increasing trend, and the level of manufacturing agglomeration showed a pattern of "strong in the east and weak in the west". The carbon emissions showed obvious spatial differentiation and concentration characteristics, showing a distribution pattern of "downstream > midstream > upstream". The spatial polarization effect was obvious.

(2) Due to the original social and economic conditions and resource endowment, the scale of carbon emissions in the Yellow River Basin showed the characteristics of path-locking, with the "club convergence" of high and low levels. The agglomeration of the manufacturing industry will increase carbon emissions, which indicates that the overall agglomeration level of manufacturing industry in the Yellow River Basin is low, and the positive externality brought by agglomeration is weak, leading enterprises to further show the characteristics of "low efficiency" and "high energy consumption".

(3) Manufacturing agglomeration has a spatial spillover effect on carbon emissions. The direct effect is significantly positive, while the indirect effect is significantly negative, indicating that manufacturing agglomeration increases carbon emissions in the region and reduces carbon emissions in neighboring regions. The manufacturing agglomeration in the Yellow River Basin is at a low stage, and the siphoning effect on neighboring areas is greater than the radiation effect, which will hinder the development of neighboring areas and reduce the carbon emissions of neighboring areas. According to the heterogeneity analysis, the manufacturing agglomeration in the lower reaches is not significant in the local carbon emissions but has an inhibitory effect on the carbon emissions in the neighboring areas.

5.2. Policy Suggestions

Climate change caused by carbon emissions has a serious impact on human life. Both developed and underdeveloped countries are actively exploring environmental governance methods suitable for their own conditions and taking various measures to achieve carbon neutrality. As a vital energy and manufacturing base, the green transformation of its manufacturing sector is critical to the green development of the Yellow River Basin. Thus, the following three suggestions are proposed.

First, we need to improve the spatial pattern of manufacturing. According to the resource endowment and economic characteristics of the regions in basin, the strategy of adapting to local conditions should be implemented to rationally allocate regional resources and carry out a rational division of labor in the industries. The concentration level of manufacturing industry in the middle and upper reaches is low, so it is necessary to further improve the talent guarantee mechanism and infrastructure construction, introduce high-level scientific talents, accelerate the concentration of human resources, build a regional advanced manufacturing industry, and attract the concentration of upstream and downstream industries. The manufacturing industry in the downstream area has a high concentration level. While improving the productivity of the region and optimizing the industrial structure, it exerts the radiation effect on the neighboring areas and promotes the coordinated development of the neighboring areas from point to point through talent exchange and knowledge spillover. Second, we should accelerate the green and low-carbon transformation of manufacturing. Under the constraint of ecological protection, the transformation and upgrading of the traditional manufacturing industry will be promoted, and the industrial structure will be adjusted in a low-carbon way to reduce energy consumption and carbon emissions [53]. Up-stream regions undertake energy-intensive industries from downstream regions, which not only promote economic growth, but also increase carbon emissions within the region, leading to the "pollution refuge" effect to a certain extent. However, the key point to change this phenomenon is not to restrict industrial transfer and spatial agglomeration of manufacturing industries, but to accelerate the merger and reorganization of small "double-high" enterprises. To change the small enterprises scattered, disorderly, excessive competition status quo, we need to give full play to the manufacturing industry agglomeration carbon emission reduction effect. The midstream manufacturing sector is at a low level of replacing old growth drivers with new ones. It needs to change the development model, optimize the economic structure, change growth drivers, and upgrade heavily polluting industries. Shandong and Henan provinces in the lower reaches are big industrial provinces with a strong manufacturing base and long history. They should timely solve the problems of industrial aging.

Third, the collaborative optimization of river basins should be strengthened. Manufacturing agglomeration has a spatial spillover effect on carbon emissions; therefore, the task of carbon emission reduction requires inter-regional collaborative governance. The upstream region should fully develop its environmental advantages, develop eco-tourism, and ease the conflict between economic development and ecological protection. The middle reaches should resolve the contradiction between resources and economic development and fulfill the role of carrying over between the upper and lower reaches. On the one hand, the downstream areas need to formulate relevant policies to optimize the energy consumption structure, reduce fossil energy consumption, and improve energy efficiency [54]. On the other hand, we should take advantage of geographical advantages to connect with the Beijing-Tianjin-Hebei region, accelerate the extension of the manufacturing industry to the middle and high end of the value chain, and radiate the middle and upper reaches of the region. It is necessary to adhere to the concept of "one game of chess" for the whole basin and pay attention to the cooperation, complementary advantages and regional linkage among provinces.

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References

1. Gleick, P.H.; Sdams, R.M.; Amasino, R.M.; Anders, E.; Anderson, D.J.; Anderson, W.W.; Anselin, L.E.; Arroyo, M.K.; Asfaw, B.; Ayala, F.J.; et al. Climate change and the integrity of science. *Science* **2010**, *328*, 689–690. [CrossRef] [PubMed]
2. Li, L.H.; Zhang, Y.; Zhou, T.J.; Wang, K.C.; Wang, C.; Wang, T.; Yuan, L.W.; An, K.X.; Zhou, C.H.; Lu, G.N. Mitigation of China's carbon neutrality to global warming. *Nat. Commun.* **2022**, *13*, 5315. [CrossRef] [PubMed]
3. Liu, Z.; Guan, D.B.; Wei, W.; Davis, S.J.; Ciais, P.; Bai, J.; Peng, S.S.; Zhang, Q.; Hubacek, K.; Marland, G.; et al. Reduced carbon emission estimates from fossil fuel combustion and cement production in China. *Nature* **2015**, *524*, 335–338. [CrossRef] [PubMed]
4. Zhao, K.; Zhang, R.; Liu, H.; Wang, G.Y.; Sun, X.L. Resource Endowment, Industrial Structu-re, and Green Development of the Yellow River Basin. *Sustainability* **2021**, *13*, 4530. [CrossRef]
5. Xin, Y.; Liu, X.Y. Coupling driving factors of eco-environmental protection and high-quality development in the yellow river basin. *Front. Environ. Sci.* **2022**, *10*, 951218. [CrossRef]
6. Xu, J.J.; Wang, H.J.; Tang, K. The sustainability of industrial structure on green eco-efficien-cy in the Yellow River Basin. *Econ. Anal. Policy* **2022**, *74*, 775–788. [CrossRef]
7. Cheng, C.; Ren, X.; Wang, Z.; Yan, C. Heterogeneous impacts of renewable energy and environmental patents on CO(2) emission—Evidence from the BRIICS. *Sci. Total Environ.* **2019**, *668*, 1328–1338. [CrossRef]
8. Ruiz-Benito, P.; Gomez-Aparicio, L.; Paquette, A.; Messier, C.; Kattge, J.; Zavala, M.A. Diversity increases carbon storage and tree productivity in Spanish forests. *Glob. Ecol. Biogeogr.* **2014**, *23*, 311–322. [CrossRef]

9. Li, R.R.; Jiang, F.; Wang, Q. The asymmetric impact of the new normal on China's carbon intensity: Reducing government investment carbon intensity but not citizen consumption carbon intensity. *Sustain. Prod. Consum.* **2022**, *32*, 895–907. [CrossRef]
10. Gao, Y.N.; Zhang, M.C.; Zheng, J.H. Accounting and determinants analysis of China's provincial total factor productivity considering carbon emissions. *China Econ. Rev.* **2021**, *65*, 101576. [CrossRef]
11. Wang, W.Z.; Hu, Y.; Lu, Y. Driving forces of China's provincial bilateral carbon emissions and the redefinition of corresponding responsibilities. *Sci. Total Environ.* **2023**, *857*, 159404. [CrossRef] [PubMed]
12. Xu, Q.; Dong, Y.X.; Yang, R.; Zhang, H.O.; Wang, C.J.; Du, Z.W. Temporal and spatial differences in carbon emissions in the Pearl River Delta based on multi-resolution emission inventory modeling. *J. Clean. Prod.* **2019**, *214*, 615–622. [CrossRef]
13. Chen, J.; Wang, L.; Li, Y. Research on the impact of multi-dimensional urbanization on China's carbon emissions under the background of COP21. *J. Environ. Manag.* **2020**, *273*, 111123. [CrossRef] [PubMed]
14. Ke, Y.H.; Xia, L.L.; Huang, Y.S.; Li, S.R.; Zhang, Y.; Liang, S.; Yang, Z.F. The carbon emissions related to the land-use changes from 2000 to 2015 in Shenzhen, China: Implication for exploring low-carbon development in megacities. *J. Environ. Manag.* **2022**, *319*, 115660. [CrossRef] [PubMed]
15. Fu, L.Y.; Wang, Q. Spatial and Temporal Distribution and the Driving Factors of Carbon Emissions from Urban Production Energy Consumption. *Int. J. Environ. Res. Public Health* **2022**, *19*, 12441. [CrossRef]
16. Wang, C.C.; Zhao, L.J.; Qian, Y.; Papageorgiou, G.N.; Lv, Y.; Xue, J. An evaluation of the international trade-related CO_2 emissions for China's light industry sector: A complex network approach. *Sustain. Prod. Consum.* **2022**, *33*, 101–112. [CrossRef]
17. Sun, W.; Huang, C.C. How does urbanization affect carbon emission efficiency? Evidence from China. *J. Clean. Prod.* **2020**, *272*, 122828. [CrossRef]
18. Zhao, J.; Shahbaz, M.; Dong, X.C.; Dong, K.Y. How does financial risk affect global CO_2 emissions? The role of technological innovation. *Technol. Forecast. Soc. Chang.* **2021**, *168*, 120751. [CrossRef]
19. Cang, D.B.; Chen, G.; Chen, Q.; Sui, L.L.; Cui, C.Y. Does new energy consumption conducive to controlling fossil energy consumption and carbon emissions?—Evidence from China. *Resour. Policy* **2021**, *74*, 102427.
20. Tang, D.L.; Peng, Z.W.; Yang, Y.H. Industrial agglomeration and carbon neutrality in China: Lessons and evidence. *Environ. Sci. Pollut. Res.* **2022**, *29*, 46091–46107. [CrossRef]
21. Song, Y.; Zhang, M. Research on the gravity movement and mitigation potential of Asia's carbon dioxide emissions. *Energy* **2019**, *170*, 31–39. [CrossRef]
22. Meng, X.N.; Xu, S.C. Can industrial collaborative agglomeration reduce carbon intensity? Empirical evidence based on Chinese provincial panel data. *Environ. Sci. Pollut. Res.* **2022**, *29*, 61012–61026. [CrossRef] [PubMed]
23. Song, J.; Li, M.Y.; Wang, S.S.; Ye, T. To What Extent Does Environmental Regulation Influence Emission Reduction? Evidence from Local and Neighboring Locations in China. *Sustainability* **2022**, *14*, 9714. [CrossRef]
24. Fontagne, L.; Santoni, G. Agglomeration economies and firm-level labor misallocation. *J. Econ. Geogr.* **2019**, *19*, 251–272. [CrossRef]
25. Cheng, Z.H. The spatial correlation and interaction between manufacturing agglomeration and environmental pollution. *Ecol. Indic.* **2016**, *61*, 1024–1032. [CrossRef]
26. Uddin, M.M.M. What are the dynamic links between agriculture and manufacturing g-rowth and environmental degradation? Evidence from different panel income countries. *Environ. Sustain. Indic.* **2020**, *7*, 100041. [CrossRef]
27. Wang-Helmreich, H.; Kreibich, N. The potential impacts of a domestic offset component in a carbon tax on mitigation of national emissions. *Renew. Sustain. Energy Rev.* **2019**, *101*, 453–460. [CrossRef]
28. Fang, J.Y.; Tang, X.; Xie, R.; Han, F. The effect of manufacturing agglomerations on smog pollution. *Struct. Chang. Econ. Dyn.* **2020**, *54*, 92–101. [CrossRef]
29. Li, H.; Liu, B.F. 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. [CrossRef]
30. Qiang, O.Y.; Wang, T.T.; Ying, D.; Li, Z.P.; Jahanger, A. The impact of environmental regulations on export trade at provincial level in China: Evidence from panel quantile regression. *Environ. Sci. Pollut. Res.* **2022**, *29*, 24098–24111. [CrossRef]
31. Zhang, Y.L.; Wang, Y.H.; Hou, X.S. Carbon Mitigation for Industrial Sectors in the Jing-Jin-Ji Urban Agglomeration, China. *Sustainability* **2019**, *11*, 6383. [CrossRef]
32. Kong, M.; Wan, H.; Wu, Q. Does Manufacturing Industry Agglomeration Aggravate Regional Pollution?—Evidence from 271 Prefecture-level Cities in China. *Glob. NEST J.* **2022**, *24*, 135–144.
33. Shen, N.; Peng, H. Can industrial agglomeration achieve the emission-reduction effect? *Socio-Econ. Plan. Sci.* **2021**, *75*, 100867. [CrossRef]
34. Lan, F.; Sun, L.; Pu, W.Y. Research on the influence of manufacturing agglomeration modes on regional carbon emission and spatial effect in China. *Econ. Model.* **2021**, *96*, 346–352. [CrossRef]
35. Matsumoto, M.; Umeda, Y. An analysis of remanufacturing practices in Japan. *J. Remanuf.* **2011**, *1*, 2. [CrossRef]
36. Giutini, R.; Gaudette, K. Remanufacturing: The next great opportunity for boosting US productivity. *Bus. Horiz.* **2003**, *46*, 41–48. [CrossRef]
37. Du, Q.; Deng, Y.G.; Zhou, J.; Wu, J.; Pang, Q.Y. Spatial spillover effect of carbon emission efficiency in the construction industry of China. *Environ. Sci. Pollut. Res.* **2021**, *29*, 2466–2479. [CrossRef]
38. Cheng, Y.; Zhang, Y.; Wang, J.J.; Jiang, J.X. The impact of the urban digital economy on China's carbon intensity: Spatial spillover and mediating effect. *Resour. Conserv. Recycl.* **2022**, *189*, 106762. [CrossRef]

39. O'Donoghue, D.; Gleave, B. A note on methods for measuring industrial agglomeration. *Reg. Stud.* **2004**, *38*, 419–427. [CrossRef]
40. Murshed, M.; Alam, R.; Ansarin, A. The Environmental Kuznets Curve Hypothesis for Bangladesh: The importance of natural gas, liquefied petroleum gas and hydropower consumption. *Environ. Sci. Pollut. Res.* **2021**, *28*, 17208–17227. [CrossRef]
41. Regmi, K.; Rehman, A. Do carbon emissions impact Nepal's population growth, energy utilization, and economic progress? Evidence from long- and short-run analyses. *Environ. Sci. Pollut. Res.* **2021**, *28*, 55465–55475. [CrossRef] [PubMed]
42. Mahmood, H.; Alkhateeb, T.T.Y.; Furqan, M. Industrialization, urbanization and CO_2 emissions in Saudi Arabia: Asymmetry analysis. *Energy Rep.* **2020**, *6*, 1553–1560. [CrossRef]
43. Rahim, S.; Murshed, M.; Umarbeyli, S.; Kirikkaleli, D.; Ahmad, M.; Tufail, M.; Wahab, S. Do natural resources abundance and human capital development promote economic growth? A study on the resource curse hypothesis in Next Eleven countries. *Resour. Environ. Sustain.* **2021**, *4*, 100018. [CrossRef]
44. Koondhar, M.A.; Shahbaz, M.; Memon, K.A.; Ozturk, I.; Kong, R. A visualization review analysis of the last two decades for environmental Kuznets curve "EKC" based on co-citation analysis theory and pathfinder network scaling algorithms. *Environ. Sci. Pollut. Res.* **2021**, *28*, 16690–16706. [CrossRef]
45. Dong, B.Y.; Ma, X.J.; Zhang, Z.L.; Zhang, H.B.; Chen, R.M.; Song, Y.Q.; Shen, M.C.; Xiang, R.B. Carbon emissions, the industrial structure and economic growth: Evidence from heterogeneous industries in China. *Environ. Pollut.* **2020**, *262*, 114322. [CrossRef]
46. Mignamissi, D.; Djeufack, A. Urbanization and CO_2 emissions intensity in Africa. *J. Environ. Plan. Manag.* **2021**, *65*, 1660–1684. [CrossRef]
47. Inkinen, T.; Kaakinen, I. Economic geography of knowledge-intensive technology clusters: Lessons from the Helsinki metropolitan area. *J. Urban Technol.* **2016**, *23*, 95–114. [CrossRef]
48. Song, H.H.; Gu, L.Y.; Li, Y.F.; Zhang, X.; Song, Y. Research on Carbon Emission Efficiency Space Relations and Network Structure of the Yellow River Basin City Cluster. *Int. J. Environ. Res. Public Health* **2022**, *19*, 12235. [CrossRef]
49. Zhang, X.Y.; Shen, M.F.; Luan, Y.P.; Cui, W.J.; Lin, X.Q. Spatial Evolutionary Characteristics and Influencing Factors of Urban Industrial Carbon Emission in China. *Int. J. Environ. Res. Public Health* **2022**, *19*, 11227. [CrossRef]
50. Chen, D.K.; Chen, S.Y.; Jin, H. Industrial agglomeration and CO_2 emissions: Evidence from 187 Chinese prefecture-level cities over 2005–2013. *J. Clean. Prod.* **2018**, *172*, 993–1003. [CrossRef]
51. Henderson, J.V. Marshall's scale economies. *J. Urban Econ.* **2003**, *53*, 1–28. [CrossRef]
52. Dong, F.; Li, Y.F.; Qin, C.; Sun, J. How industrial convergence affects regional green development efficiency: A spatial conditional process analysis. *J. Environ. Manag.* **2021**, *300*, 113738. [CrossRef] [PubMed]
53. Jin, B.L.; Han, Y. Influencing factors and decoupling analysis of carbon emissions in China's manufacturing industry. *Environ. Sci. Pollut. Res.* **2021**, *28*, 64719–64738. [CrossRef]
54. Yuan, X.L.; Sheng, X.R.; Chen, L.P.; Tang, Y.Z.; Li, Y.; Jia, Y.S.; Qu, D.F.; Wang, Q.S.; Ma, Q.; Zuo, J. Carbon footprint and embodied carbon transfer at the provincial level of the Yellow River Basin. *Sci. Total Environ.* **2022**, *803*, 149993. [CrossRef] [PubMed]