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Explore the Role of Synergy Agglomeration between Producer Services and Manufacturing Industry on Carbon Productivity

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Abstract

This paper, based on the provincial data of China from 2012 to 2022, employs a two-way fixed panel model to empirically study the impact effect and transmission mechanism of the collaborative agglomeration of manufacturing and producer services on regional carbon productivity. The study finds that: the collaborative agglomeration of manufacturing and producer services can significantly enhance regional carbon productivity, with a clear function of energy saving, carbon reduction, and efficiency improvement. Non-linear impact analysis reveals that the relationship between the two presents a distinct "U" shape, with the promotional effect strengthening after passing the inflection point. Heterogeneity analysis shows that regions at different levels of manufacturing agglomeration and producer services agglomeration exhibit varying degrees and significance of impact on carbon productivity from the enhancement of the two industries' collaborative agglomeration, and the inflection points where the effect strengthens are also inconsistent. The analysis of transmission mechanisms reveals that the collaborative agglomeration of the two industries can always influence carbon productivity by promoting the optimization of factor structure, industry scale expansion, and technological progress, while the impact on industrial structure optimization and technological efficiency optimization presents a "U" shape, characterized by long-term and dynamic nature.

Keywords

Industrial Collaborative Agglomeration; Carbon Productivity; EBM-GML.

1. Introduction

With the increasing prominence of constraints such as resources, environment, institutions, and innovation, the advantages of traditional manufacturing are gradually diminishing. The congestion effect brought about by agglomeration becomes dominant, leading to severe issues such as abnormal climate change and intensified environmental pollution, resulting in a situation where high industrial agglomeration and high environmental pollution coexist [1]. In response, the characteristics of industrial agglomeration in countries around the world have gradually shifted from the agglomeration of a single industry to the collaborative agglomeration of related industries. The collaborative agglomeration of producer services and manufacturing (hereinafter referred to as the synergy of the industries) is one of the main manifestations. Carbon emissions, as a major environmental variable constraining global development, measure the economic benefits a country generates by consuming a unit of carbon resources over a period of time [2]. Incorporating the element of carbon (carbon emission space) into the input-output framework, the expectation is to achieve the maximum output with the least carbon input [3]. This paper intends to analyze the specific impact mechanism between the synergy of the two industries in China and carbon productivity.

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2. Mechanism Analysis

This article finds that the collaborative agglomeration of two industries can affect carbon emissions through four effects: technological innovation effect, structural optimization effect, efficiency optimization effect, and scale expansion effect. First, collaborative agglomeration between the same or different industries will obtain specialization in division of labor and technological externalities, promoting the integration and innovation of products, services, and technologies, thereby improving carbon productivity [4]. Second, the structural optimization effect includes the optimization of factor structure and industrial structure. The deepening of specialization in division of labor continuously generates new intermediate departmental industries, with the types and structure of industries constantly changing, the industrial chain continuously upgrading, and the industrial structure continuously optimizing [5]. This not only updates its refined requirements for traditional factors such as labor, technology, and energy but also accelerates the integration of services, digital, and other factors into all stages of the product life cycle, significantly improving enterprise resource utilization and carbon productivity [6]. Finally, the collaborative agglomeration of two industries accelerates the realization of economies of scope and economies of scale, continuously expanding the output scale of productive services and manufacturing while increasing their energy consumption. When the efficiency improvement brought by economies of scale is greater than the increase in energy consumption, it will improve carbon productivity, and vice versa, it will suppress carbon productivity [7]. As the scale continues to expand, the collaborative agglomeration of two industries will bring about the crowding effect of factors, reducing the precision of productive services, and also suppressing carbon productivity.

3. Variable Measurement

3.1. The Coordinated Agglomeration of Industries. Carbon Productivity

This paper represents the total of the wholesale industry, transportation, warehousing, and postal services, information transmission, software and information technology services, finance, leasing and business services, scientific research and technical services, and ecological environmental protection and environmental management industry as the productive service industry [8]. From the perspective of industrial geography layout, it uses location entropy to measure the level of synergistic agglomeration of manufacturing and productive services [9], as shown in Equation (1):

$$LQ_{imt} = \frac{q_{imt}/q_{mt}}{q_{it}/q_t} \tag{1}$$

Where LQ_{imt} is the location entropy of industry i in region m in year t, q_{imt} is the number of employees in industry i in region m in year t, q_{mt} is the number of employees in manufacturing and productive services in region m in year t, q_{it} is the total number of employees in industry i in year t, and q_t is the total number of employees in manufacturing and productive services across the country in year t. This paper uses the number of urban unit employees in manufacturing and productive services to represent the number of employees in each industry. Then, it calculates the level of synergistic agglomeration of manufacturing (M) and productive services (PS), as shown in Equation (2):

$$Cogg_{mt} = \left(1 - \frac{|LQ_{M,mt} - LQ_{PS,mt}|}{LQ_{M,mt} + LQ_{PS,mt}}\right) + |\delta_1 LQ_{M,mt} + \delta_2 LQ_{PS,mt}| \tag{2}$$

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where $LQ_{M,mt}$ represents the agglomeration degree of manufacturing in region m, and $LQ_{PS,mt}$ represents the agglomeration degree of productive services in region m. δ_1 and δ_2 are correction coefficients for the location entropy of manufacturing and productive services, respectively, measured by the ratio of the value added of the secondary and tertiary industries to the regional gross product. The larger the value of $Cogg_{mt}$, the higher the level of synergistic agglomeration between the two industries, and the smaller the difference between manufacturing and productive services in region m [10].

3.2. Carbon Productivity

This paper refers to Y.N. Zheng et al. (2024) and uses the EBM-GML model to measure the total factor carbon productivity at the provincial level [11]. It is assumed that there are n decision-making units DMU, m input factors, q desired output factors, and v undesired output factors. The input factors include labor input, capital input, and energy input. The desired output is the level of regional economic development, and the undesired output is the regional carbon emission situation, as shown in Table 1:

Table 1. Input-Output Indicators and Definitions

Indicator	Variable	Definition	Unit
Input	Labor Input	Employment figures	Ten thousand people
	Capital Input	Fixed capital stock (constant prices of 2012)	Ten thousand yuan
	Energy Input	Total Energy Consumption	Ten thousand tons of standard coal
Output	Desired Output	Actual GDP (constant prices of 2012)	Ten thousand yuan
	Undesired Output	Carbon dioxide emissions	Ten thousand tons

Table 2. Carbon dioxide emission coefficients for various emission sources

Carbon emission sources		CF_h	CC_h	COF_h	Carbon Emission Coefficient	CO2 Emission Coefficient
		TJ/Ten thousand t(billion m^3)	tC/TJ	-	tC/t (Ten thousand m^3)	tCO2/t(Ten thousand m^3)
Fossil Energy Consumption	Coal	178.240	27.280	0.923	0.449	1.647
	Coke	284.350	29.410	0.928	0.776	2.848
	Gasoline	448.000	18.900	0.980	0.830	3.045
	Kerosene	447.500	19.600	0.986	0.865	3.174
	Diesel	433.300	20.170	0.982	0.858	3.150
	Fuel oil	401.900	21.090	0.985	0.835	3.064
	Natural gas	3893.100	15.320	0.990	5.905	21.670
Cement Production	Cement	-	-	-	-	0.527

① Labor input. Represented by the number of employed personnel at the end of the year in various administrative units.② Capital input. Following the method of H.J. Shan (2008), the fixed capital stock is represented using the perpetual inventory method with 2012 as the base

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period [12]. The calculation formula is $K_{mt} = K_{mt-1}(1-\delta_{mt}) + I_{mt}$, where I_{mt} is the total fixed capital formation in region m in year t, K_mt is the capital stock in region m in year t, and δ_mt is the depreciation rate in region m in year t, taken as 10.96%.③ Energy input. Represented by the total energy consumption of each province.④ Desired output. Represented by the actual GDP of each province.⑤ Undesired output. Represented by the carbon dioxide emissions of each province, following the estimation method of L.M. Du (2010). First, estimate the carbon dioxide emissions from fossil fuel consumption using $C = \sum_{h=1}^{6} EC_h = \sum_{h=1}^{6} E_h \times CF_h \times CC_h \times COF_h \times 3.67$, where h represents the type of energy consumption, E_h represents the total consumption of the hth type of energy in a region, $CF_h \times CC_h \times COF_h$ represents the carbon emission coefficient, and $CF_h \times CC_h \times COF_h \times 3.67$ represents the carbon dioxide emission coefficient. Second, measure the carbon dioxide emissions from cement production using $CC = Q \times EF_C$, where Q represents the total cement production, and EF_C represents the carbon dioxide emission coefficient of cement production [13]. The carbon dioxide emission coefficients for various emission sources are shown in Table 2.

x_{ik}, y_{rk}, and h_{pk} are the vector forms of these three types of elements, and s_i^-, s_r^+, and s_p^{h-} are their slack variables. Under the assumption of variable returns to scale (VRS), the linear programming expression for the EBM model considering non-desired outputs is Equation (3):

$$\gamma^* = \min_{\theta,\lambda,s^-} \frac{\theta - \varepsilon_x \sum_{i=1}^{m} \frac{w_i^- s_i^-}{x_{ik}}}{\varphi + \varepsilon_y \sum_{r=1}^{q} \frac{w_r^+ s_r^+}{y_{rk}} + \varepsilon_h \sum_{p=1}^{v} \frac{w_p^{h-} s_p^{h-}}{h_{pk}}} \tag{3}$$

$$s.t.\begin{cases} \theta x_{ik} - \sum_{j=1}^{n} x_{ij}\lambda_j - s_i^- = 0, i = 1,2,\dots,m; \\ \varphi y_{rk} - \sum_{j=1}^{n} y_{rj}\lambda_j - s_r^+ = 0\,, r = 1,2,\dots,q; \\ \varphi h_{pk} - \sum_{j=1}^{n} h_{pj}\lambda_j - s_p^{h-} = 0, p = 1,2,\dots,v; \\ \lambda, s^-, s^+ \gg 0 \\ \sum_{i=1}^{m} w_i^- = 1 \\ 0 \le \varepsilon_x \le 1 \end{cases}$$

In this context, γ^* represents the optimal efficiency value of the EBM model measure, which is the static efficiency of the total factor carbon productivity; θ represents the radial efficiency value; x_{ik}, y_{rk}, and h_{pk} represent the input, expected output, and undesired output vectors of the kth DMU, respectively; λ represents the relative weight of the input factors; s_i^- represents the non-radial slack variable for the i-th input factor; w_i^- represents the weight of the i-th input factor; ε_x is the key parameter that combines radial variation and non-radial slack vectors; s_r^+ and s_p^{h-} represent the slack vectors for the r-th expected output and the p-th undesired output, respectively. If their values are greater than0, it indicates that the actual inputs and outputs are below the production frontier boundary level, and there is room for efficiency improvement; w_r^+ and w_p^{h-} represent the weights of the r-th expected output and the p-th undesired output, respectively. Weights are assigned using MATLAB software based on original data to avoid the bias of subjective weighting.

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To further analyze the dynamic changes in total factor productivity across regions, this paper calculates the GML index using the formula: $GML_t^{t-1} = \frac{1+D_0^G(x^t,y^t,b^t,y^t,-b^t)}{1+D_0^G(x^{t+1},y^{t+1},b^{t+1},y^{t+1},-b^{t+1})}$. If the GML index for a given period is greater than1, it indicates that the total factor productivity index for that period has increased compared to the previous period. The GML index can be decomposed into the technological progress index (TC) and the efficiency optimization index (EC). EC represents the speed at which the actual output level of the production decision unit catches up to the maximum output level, while TC represents the speed at which the production decision unit progresses towards the technological frontier. When the values of GML, EC, and TC are all greater than 1, it indicates that the total factor carbon productivity, production efficiency, and technological level of the region have improved relative to the previous year.

4. Research Design

Existing literature on the relationship between industrial collaborative agglomeration and carbon emissions has not reached a consensus, with some scholars arguing for a simple linear relationship, while others conclude it to be an inverted "U-shaped" or "N-shaped" relationship. Based on the collection and organization of panel data from Chinese provinces from2012 to2022, this paper estimates the index of collaborative agglomeration of two industries (cogg) as the core explanatory variable and total factor carbon productivity (cp) as the dependent variable, constructing the following econometric model to conduct an empirical study on the impact of collaborative agglomeration of two industries on regional carbon productivity.

$$lncp_{it} = \beta_0 + \beta_1 lncogg_{it} + \beta_2 X_{it} + \varepsilon_{it} \tag{4}$$

Subsequently, this paper introduces the quadratic term of the core explanatory variable to further test the non-linear relationship between the two.

$$lncp_{it} = \beta_0 + \beta_1 lncog_{it} + \beta_2 lncogg2_{it} + \beta_4 X_{it} + \varepsilon_{it} \tag{5}$$

In the above formula, $lncp_{it}$ represents the carbon productivity of province i in year t, $lncogg_{it}$ represents the level of collaborative agglomeration of two industries in province i in year t, X_{it} represents the control variables, and ε_{it} represents the random disturbance term.The selection of control variables refers to X.P. Liu (2019) and H.F. Yue et al. (2017), introducing research and development investment (rd), foreign direct investment (fdi), human capital level (hc), government intervention (gov), and industrial enterprise scale (fs), all taken in logarithmic form [14,15].

5. Result Analysis

5.1. Descriptive Statistics

The descriptive statistics of the main variables are shown in Table 3. The standard deviation of the logarithmic value of carbon productivity is 0.224, indicating that there is a significant difference in the practical effects of reducing carbon emissions and improving carbon productivity among different provinces, and the attention to carbon reduction and efficiency enhancement varies. The mean of carbon productivity is 1.139, which is close to the minimum value, and the maximum value reaches 2.162. This not only indicates that there are leading areas and pioneers in improving carbon productivity among provinces, but also suggests that most provinces have slow effects in improving carbon productivity and may need to further play a leading and synergistic role. The data characteristics of the two industries' collaborative

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agglomeration are similar to those of carbon productivity, but the minimum value and mean are both higher, indicating that the attention and awareness of provinces to industrial collaborative agglomeration are significantly greater than those in green and low-carbon aspects. Among the control variables, the standard deviation values of foreign investment, human capital, industrial enterprise scale, and government intervention are all relatively large, similar to carbon productivity, and all exhibit regional imbalances in development. This may suggest that improving the norms of foreign capital utilization, optimizing the training mechanism of human capital, promoting the development of small and medium-sized industrial enterprises, and enhancing the efficiency of government intervention may be conducive to improving carbon productivity and accelerating the green and low-carbon transformation and development of regions.

Table 3. Descriptive Statistical Results of the Main Variables

Variable	Definition	N	Mean	SD	Min	Max
cp	See 3.1	330	1.139	0.224	0.818	2.162
cogg	See 3.2	330	1.733	0.121	1.379	2.059
rd	Fiscal expenditure on science and technology / Total fiscal expenditure	330	0.022	0.015	0.005	0.068
fdi	Total investment of foreign-invested enterprises / GDP	330	0.875	4.318	0.048	55.358
hc	Number of college students per 100,000 population	330	2812.624	844.139	1133.000	5534.000
fs	Main business revenue of large-scale industrial enterprises /GDP	330	1.263	0.469	0.389	2.819
gov	Total fiscal expenditure /GDP	330	0.260	0.111	0.105	0.758

5.2. Benchmark Regression Analysis

After conducting F-tests, LM tests, and Hausman tests, this paper controls for individual and time fixed effects, and gradually introduces control variables into the regression, with the results shown in Table 4.The level of synergy between the two industries in each province is positively correlated with carbon productivity, significant at the 5% level, indicating that a 1% increase in the level of synergy between the two industries can significantly increase regional carbon productivity by 0.3418%, which is consistent with the conclusions of H. Xu et al. (2023) [16]. After taking logarithmic stable data and introducing control variables, this phenomenon remains significant, and the estimated coefficient size of the synergy between the two industries has increased. Referring to the study of Y. Wang et al. (2020) on the relationship between industrial synergy and productivity, column (4) reveals a "U"-shaped relationship between the level of synergy between the two industries and carbon productivity. It can be observed that the estimated coefficient of the synergy between the two industries is negative, and the estimated coefficient of the quadratic term of the synergy between the two industries is positive, both significant at the 1% level, indicating that increasing the level of synergy between the two industries in each province will have a suppressive effect on regional carbon productivity first and then a promotional effect, consistent with the conclusions of H. Xu et al. (2023) [17]. The synergy between manufacturing and production services is a dynamic process. As production services join the agglomeration, the manufacturing industry chain gradually enriches, and the value chain gradually climbs. However, in the early stages of agglomeration, due to the high energy consumption, high pollution, and high emission characteristics of the highly concentrated manufacturing industry, more factor inputs have not achieved significant pollution reduction and emission reduction effects, and carbon productivity decreases. When the synergy reaches a certain level, production services are highly integrated into

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manufacturing, truly innovating manufacturing production technology, optimizing production efficiency, and reconstructing the production process, achieving effective improvement of carbon productivity. The "U"-shaped turning point of the impact of the synergy between the two industries on carbon productivity is 1.6588 (lncoggy=0.5061). When the level of synergy between the two industries is less than 1.6588, the synergy between the two industries reduces carbon productivity. When the level of synergy between the two industries is greater than 1.6588, the synergy between the two industries increases carbon productivity. The overall average level of synergy between the two industries in the country is around 1.7200, indicating that most provinces have crossed the inflection point. However, the level of synergy between the two industries in Tibet, Heilongjiang, Xinjiang, Inner Mongolia, and other places has not yet made a positive contribution to carbon productivity. Among the control variables, increasing local fiscal science and technology expenditure has not achieved the effect of improving carbon productivity, which may be due to the long cycle, lag effect, and uncertainty of technology development to the final application, and cannot be targeted. At the current stage, improving the level of human capital will reduce carbon productivity, indicating that the improvement of carbon productivity requires disruptive innovation in education functions and human capital functions, and needs to increase investment in green and low-carbon disciplines and skill fields. At the current stage, increasing business income and scale of industrial enterprises will reduce carbon productivity overall, indicating that regional carbon dioxide emissions mainly come from large-scale industries, and it is necessary to balance and adjust the carbon reduction and efficiency increase of large enterprises and give full play to the role of small and medium-sized enterprises.

Table 4. Benchmark Regression Results

	(1)	(2)	(3)	(4)
	cp	lncp	lncp	lncp
cogg	0.3418**			
	(0.1630)			
lncogg		0.3818*	0.4303**	-5.3312***
		(0.2259)	(0.2049)	(1.0556)
lncogg2				5.2668***
				(0.9615)
lnrd			-0.1176***	-0.1138***
			(0.0245)	(0.0232)
lnfdi			0.0052	-0.0078
			(0.0209)	(0.0215)
lnhc			-0.1854**	-0.2183**
			(0.0880)	(0.0850)
lnfs			-0.1384***	-0.1390***
			(0.0438)	(0.0412)
lngov			-0.0465	-0.0698
			(0.0846)	(0.0833)
_cons	0.5473*	-0.0950	0.8318	2.6091***
	(0.2825)	(0.1239)	(0.7477)	(0.7983)
Individual Fixed	Yes	Yes	Yes	Yes
Time Fixed	Yes	Yes	Yes	Yes
N	330	330	330	330
adj. R^2	0.6899	0.7307	0.7708	0.7874

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5.3. Robustness Test

To further examine the relationship between the synergy and agglomeration of two industries and carbon productivity, this paper replaces the explained variable and the core explanatory variable and re-runs the regression. The results are shown in Table 5. cp1 continues to use the input-output framework of cp, but takes the amount of carbon dioxide emissions as the carbon space input, introduces the climate risk index as an undesired output, and then calculates the EBM-GML index, with 2012 as the base period for cumulative multiplication. cog refers to the industrial synergy and agglomeration index Θ as represented by J.J. Chen et al. (2016): $\Theta_{ij} = 1 - \frac{|\eta_{im}-\eta_{jm}|}{|\eta_{im}+\eta_{jm}|} + (\eta_{im} + \eta_{jm})$. The estimated coefficients of the two industries' synergy and agglomeration and the quadratic term of the two industries' synergy and agglomeration are roughly equivalent in magnitude and significance to the benchmark conclusions, further supporting the robustness of the benchmark conclusions.

Table 5. Change variables

	(1)	(2)	(3)	(4)	(5)	(6)
	lncp1	lncp1	lncp1	lncp1	lncp1	lncp1
lncogg	0.5629***	0.5848***	-4.6931***			
	(0.2410)	(0.2212)	(1.1601)			
lncogg2			4.8248***			
			(1.0502)			
lncog				0.5567**	0.5849***	-4.2029***
				(0.2364)	(0.2173)	(1.1488)
lncog2						4.3812***
						(1.0321)
_cons	-0.1806	0.6383	2.2664***	-0.1772	0.6542	2.1213**
	(0.1323)	(0.7770)	(0.8412)	(0.1297)	(0.7742)	(0.8442)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Individual Fixed	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed	Yes	Yes	Yes	Yes	Yes	Yes
N	330	330	330	330	330	330
adj. R^2	0.7436	0.7790	0.7913	0.7436	0.7792	0.7903

Considering that the national economic industry classification standards were revised in 2017, this paper excludes that year and conducts regression, with the results shown in columns (1)-(2) of Table 6. Subsequently, following the majority of literature, this paper regresses on all variables after applying a1% two-tailed trimming, with the results shown in columns (3)-(4) of Table 6. The estimated coefficients of Lncogg and lncogg2 are still similar to the characteristics of the benchmark results, indicating the robustness of the benchmark conclusions. Considering the endogeneity issues such as omitted variable bias and bidirectional causality, which may lead to biased conclusions regarding the "U"-shaped relationship between lncogg and lncp. This paper, in line with the majority of literature, introduces a one-period lagged term of the core explanatory variable as an instrumental variable (IV) for 2SLS estimation, with results shown in columns (5)-(6) of Table 6 [18]. The Kleibergen-Paap rk LM statistic rejects the null hypothesis of the IV being unidentifiable at the 1% level, suggesting that the IV is identifiable. The Kleibergen-Paap rk Wald F statistic is greater than the 10% critical value of Stock-Yogo, indicating that there is no weak instrument problem. After accounting for endogeneity, the estimated effect of the two industries' collaborative agglomeration on carbon productivity

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remains similar in magnitude, direction, and significance to the baseline regression, enhancing the reliability of the baseline conclusion.

Table 6. Other robustness methods

	(1)	(2)	(3)	(4)	(5)	(6)
	lncp	lncp	lncp	lncp	lncp	lncp
lncogg	0.4711**	-5.1051***	0.4303**	-5.3312***	-7.9708***	-7.9708***
	(0.2133)	(1.0713)	(0.2049)	(1.0556)	(2.3370)	(2.3370)
lncogg2		5.0940***		5.2668***		7.5739***
		(0.9792)		(0.9615)		(1.9963)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Individual Fixed	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed	Yes	Yes	Yes	Yes	Yes	Yes
N	330	330	330	330	330	330
F	-	-	-	-	75.2700 (0.0000)	55.0400 (0.0000)
Kleibergen-Paap rk LM	-	-	-	-	51.3790 (0.0000)	32.0610 (0.0000)
Kleibergen-Paap rk Wald F	-	-	-	-	75.2690 (16.3800)	9.6300 (7.0300)
adj. R2	0.5168	0.5533	0.7599	0.7761	0.0135	0.0488

6. Heterogeneity Analysis

As the scale of agglomeration continues to expand, enterprises within the agglomeration space face limitations in market capacity, geographical space, and resources, leading to a congestion effect that inhibits the improvement of economic efficiency [19]. Therefore, the effects of the synergistic agglomeration of manufacturing and producer services may vary at different stages of agglomeration in these two industries.

6.1. Heterogeneity in the Level of Manufacturing Industry Agglomeration

This paper first divides high and low levels of manufacturing agglomeration based on the median of manufacturing agglomeration(LQM), and the regression results are shown in Table 7 columns (1)-(4). In the low level of manufacturing agglomeration stage, collaborative agglomeration has a positive and significant impact on regional carbon total factor productivity, while it is not significant in the high agglomeration level stage. From the perspective of non-linear relationships, the "U"-shaped impact and significance of manufacturing enterprises at the low level of manufacturing agglomeration and productive service enterprises' collaborative agglomeration on carbon productivity are both less than those at the high level of manufacturing agglomeration. This indicates that high manufacturing agglomeration is in the mature stage of the agglomeration life cycle theory, with a large demand for production factors, and excessive concentration of energy and other factors may lead to congestion effects and a large amount of pollution emissions. In the initial stage of collaborative agglomeration of enterprises and productive service enterprises, it cannot effectively improve the environment and enhance carbon productivity. However, enterprises at the high level of manufacturing agglomeration, due to their rich agglomeration practices, may accelerate the collaborative agglomeration process and improve the quality of collaborative agglomeration, thus better playing the role of collaborative agglomeration in reducing carbon and increasing efficiency, and carbon productivity is improved.

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6.2. Heterogeneity in the Agglomeration Level of Producer Services

This paper further divides high and low levels of production-oriented service industry agglomeration based on the median value of agglomeration(LQPS), and the regression results are shown in Table 7 columns (5)-(8). In the low production-oriented service industry agglomeration stage, collaborative agglomeration has no significant impact on regional carbon total factor productivity, while in the high agglomeration level stage, it has a significant positive impact. From the perspective of non-linear relationships, the "U"-shaped impact and significance of production-oriented service enterprises at the low production-oriented service industry agglomeration level and manufacturing industry collaborative agglomeration on carbon productivity are greater than those at the high manufacturing industry agglomeration level stage. This indicates that enterprises at the high production-oriented service industry agglomeration level and manufacturing enterprises' collaborative agglomeration, which is equivalent to introducing advanced technology, high-quality transportation services, and precise financial services and other production-oriented services into manufacturing enterprises in a timely manner, can greatly promote the improvement of carbon productivity in the short term. However, as the degree of collaborative agglomeration deepens, enterprises at the high production-oriented service industry agglomeration level face challenges such as reconstructing the agglomeration pattern and improving the agglomeration mechanism, in order to form a more suitable collaborative agglomeration situation with an increasing number of manufacturing enterprises, thereby better enhancing carbon productivity.

Table 7. Regression Results Grouped by Agglomeration Level

	Low LQM		High LQM		Low LQPS		High LQPS	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	lncp	lncp	lncp	lncp	lncp	lncp	lncp	lncp
lncogg	1.0675***	-3.6836*	0.1122	-7.1750***	0.0449	-6.0785***	1.1915***	-4.0438*
	(0.3463)	(2.1902)	(0.2490)	(1.9484)	(0.2055)	(1.7899)	(0.3512)	(2.2702)
lncogg2		4.1752**		6.9027***		5.8121***		4.6217**
		(1.8082)		(1.8155)		(1.6672)		(1.9042)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual Fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	165	160	165	160	161	165	161	165
adj. R2	0.8052	0.7931	0.8122	0.8273	0.8415	0.7949	0.8619	0.8047

7. Mechanism Path Analysis

This paper refers to S.J. Zhu et al. (2020) to use the capital-labor ratio (kl) to measure the optimization effect of factor structure, and uses the ratio of total industrial output value to regional gross product (gy) to measure the scale expansion effect [20]. Following most literature, the ratio of the added value of the tertiary industry to the added value of the secondary industry is used to measure the optimization effect of industrial structure. Columns (1)-(2) of Table 8 test the path of the industrial structure optimization effect, and the results show that the collaborative agglomeration of the two industries has a significant "U"-shaped impact on industrial structure optimization. Industrial structure upgrading, as the basic support for energy saving and carbon reduction, will affect carbon productivity through the optimization effect of industrial structure [21]. The turning point is lncogg=0.5773. Columns (3)-(4) test the path of the factor structure optimization effect, and the results show that the collaborative agglomeration of the two industries can significantly reduce the gap between capital and labor, optimize the factor structure, and when lncogg exceeds0.4884, the effect of

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factor structure optimization is stronger. Columns (5)-(6) test the path of the scale expansion effect, and the results show that the collaborative agglomeration of the two industries can significantly enhance the scale of the industrial sector. A higher industry scale is conducive to the industry's own supervision and pollution control, thereby affecting carbon productivity [15]. The nonlinear characteristics of the scale expansion effect are "U"-shaped, with the inflection point at 0.4832.

Table 8. Conduction Mechanism Regression Results

	(1)	(2)	(3)	(4)	(5)	(6)
	lnind	lnind	lnkl	lnkl	lngy	lngy
lncogg	-0.1280	-2.4355*	-0.5205*	4.3416**	0.5097***	-3.8651***
	(0.1629)	(1.2845)	(0.2657)	(1.8770)	(0.1964)	(1.4042)
lncogg2		2.1094*		-4.4446***		3.9991***
		(1.1462)		(1.6723)		(1.2547)
cons	2.6127***	3.3246***	1.3351	-0.1648	-2.6355***	-1.2859
	(0.5807)	(0.7219)	(1.1002)	(1.3183)	(0.7621)	(0.8805)
Individual Fixed	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed	Yes	Yes	Yes	Yes	Yes	Yes
N	330	330	330	330	330	330
adj. R2	0.9590	0.9594	0.9418	0.9429	0.8982	0.9012

This paper refers to S.J. Zhu et al. (2020) to use the technological progress index of carbon productivity to measure the effect of technological innovation, and refers to J. Zhang et al. (2023) to further identify the sources of carbon productivity growth promoted by the collaborative agglomeration of two industries based on the internal composition of carbon productivity [20,22]. ec and tc are the technical efficiency index and technological progress index obtained from the decomposition of carbon productivity, respectively, and the regression results are shown in Table 9 Columns (1)-(4) indicate that the collaborative agglomeration of two industries has no significant linear impact on the internal technical efficiency of carbon productivity, but there is a significant "U"-shaped impact relationship, while the collaborative agglomeration of two industries has a significant positive impact on the internal technological progress of carbon productivity, and the "U"-shaped impact relationship is slightly weaker than the internal technical efficiency. Technical efficiency refers to the impact on resource allocation efficiency caused by changes in environmental factors due to policy and institutional changes, while technological progress refers to the advancement of technology pushing the frontier of production outward. Therefore, increasing technological innovation has a continuous enhancing effect on carbon productivity, and the improvement and optimization of resource allocation efficiency by the collaborative agglomeration of two industries is a long-term process, showing a trend of first decreasing and then increasing. Specifically, when lncogg is greater than 0.5227, the collaborative agglomeration of two industries can significantly improve technical efficiency, but the collaborative agglomeration of two industries always significantly promotes technological progress, and when lncogg is greater than 0.4804, this promoting effect is further strengthened and the magnitude is further increased. Therefore, the source of carbon productivity growth promoted by the collaborative agglomeration of two industries comes from its promotion of technological progress and improvement of technical efficiency. Among them, the source of the non-linear relationship between the collaborative agglomeration of two industries and carbon productivity mainly comes from the improvement of internal technical

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efficiency and internal technological progress, and the source of the positive linear relationship mainly comes from internal technological progress.

Table 9. Internal Analysis of Carbon Productivity Composition

	(1)	(2)	(3)	(4)
	lnec	lnec	lntc	lntc
lncogg	0.1602	-3.4452***	0.2745**	-1.9795**
	(0.1443)	(0.6421)	(0.1143)	(0.7704)
lncogg2		3.2958***		2.0604***
		(0.5769)		(0.6992)
_cons	0.7469	1.8591***	-0.0038	0.6915
	(0.4873)	(0.4806)	(0.5416)	(0.6430)
Individual Fixed	Yes	Yes	Yes	Yes
Time Fixed	Yes	Yes	Yes	Yes
N	330	330	330	330
adj. R2	0.7027	0.7190	0.7554	0.7600

8. Conclusion

This paper, based on provincial data in China from2012 to 2022, employs a two-way fixed panel model to empirically study the impact effect and transmission mechanism of the collaborative agglomeration of manufacturing and producer services on regional carbon productivity. The study finds that:

The collaborative agglomeration of manufacturing and producer services can significantly enhance regional carbon productivity, with a clear function of energy saving, carbon reduction, and efficiency improvement. Further research into the non-linear relationship reveals a "U"-shaped relationship between the collaborative agglomeration of manufacturing and producer services and regional carbon productivity, with the national average inflection point at lnCOGG of0.5601, indicating that the promotional effect strengthens when lnCOGG exceeds0.5601.

After heterogeneity analysis based on the agglomeration levels of manufacturing and producer services, it is found that the impact of the enhancement of collaborative agglomeration on carbon productivity varies in magnitude and significance based on different agglomeration levels, and the inflection points of the effect enhancement are also inconsistent. For manufacturing agglomeration, the enhancement of collaborative agglomeration between enterprises with low manufacturing agglomeration levels and producer service enterprises has a relatively rapid effect on the improvement of regional carbon productivity, but the inflection point of lnCOGG is also lower, and when it reaches0.4411, the significance of the improvement is somewhat mitigated; for enterprises with high manufacturing agglomeration levels, the enhancement of collaborative agglomeration with producer service enterprises has a significant and substantial effect on regional carbon productivity when lnCOGG reaches0.5197. For producer service agglomeration, the conclusion is the opposite, with the inflection point of lnCOGG at0.5227 for low producer service agglomeration levels and0.4375 for high producer service agglomeration levels.

Regarding the impact path of the collaborative agglomeration of manufacturing and producer services on carbon productivity, the paper finds that the two types of collaborative agglomeration can always promote the optimization of factor structure, industry scale expansion, and technological progress, thereby affecting carbon productivity. Their impact on industrial structure optimization and technical efficiency optimization shows a clear "U"-shaped characteristic, with long-term and dynamic features. After comparing the non-linear

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inflection points of the four effects, the inflection point of the technological progress effect is the lowest at lnCOGG=0.4804, followed by the scale expansion effect at lnCOGG=0.4832, then the factor structure optimization effect at lnCOGG=0.4884, the technical efficiency optimization effect at lnCOGG=0.5227, and finally the industrial structure optimization effect at lnCOGG=0.5773. At the current stage, the technological progress effect, scale expansion effect, factor structure optimization effect, and technical efficiency optimization effect are the main transmission paths for the collaborative agglomeration of the two industries to promote regional carbon productivity, and the average level of collaborative agglomeration has not yet passed the inflection point of the industrial structure optimization effect.

To promote the collaborative agglomeration of manufacturing and producer services, enhance regional carbon productivity, and advance regional economic green and low-carbon transformation, this paper proposes three policy recommendations based on the above conclusions: First, to enhance the collaborative agglomeration level of manufacturing and producer services in various regions according to local conditions, it is necessary to explore brand-name manufacturing or producer services and promote regions such as Tibet, Heilongjiang, Xinjiang, and Inner Mongolia to pass the inflection point. Second, enhancing the collaborative agglomeration level of manufacturing and producer services in various regions should be based on the agglomeration trends of manufacturing and producer services in each region, accurately locate the regional agglomeration characteristics, and then customize measures to promote the collaborative agglomeration of the two industries. For example, regions with high manufacturing agglomeration and high producer service agglomeration should focus on the subjective initiative of producer service enterprises when promoting the collaborative agglomeration of the two industries, thereby achieving a significant improvement in carbon productivity. Third, the factor structure optimization effect of the collaborative agglomeration of manufacturing and producer services is relatively strong and significant, and each region should dynamically adjust the level of collaborative agglomeration based on the region's technological attributes, resource attributes, and industrial attributes, striving to play a relatively optimal effect and effectively improve carbon productivity.

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