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Advancing towards a low-carbon urban future in China: the role of producer services agglomeration

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The reduction of greenhouse gas emissions is a shared challenge encountered by nations worldwide. As China is on its way toward a green economy, it is worth studying whether producer services agglomeration, a key driver of economic transition, can promote low-carbon urban development. Using panel data of 257 cities across China from 2006 to 2019, this paper examines the influence of producer services agglomeration on urban carbon emissions with spatial econometric models. The findings reveal a positive spatial correlation in regional carbon emissions. The agglomeration of producer services notably decreases the intensity of local carbon emissions, yet it appears to have minimal influence on the emissions from adjacent regions. Enhancing energy efficiency and adjusting the industrial structure are two critical mechanisms by which producer services agglomeration reduces urban carbon emissions. This beneficial effect varies with city type, the abatement effect of producer services agglomeration is more pronounced in non-resource-based cities. When considering city size, the carbon reduction potential of producer services agglomeration is not apparent in smaller cities. As city size increases, the emission reduction effect becomes more apparent. However, in mega-cities, this impact is somewhat diminished. Accordingly, this paper proposes exploring methods of coordinated air pollution management across cities, promoting producer services agglomeration in line with market mechanisms, and driving low-carbon urban development in a manner tailored to local conditions.

KEYWORDS

producer services agglomeration, industrial structure adjustment, energy efficiency improvement, carbon emission intensity, spatial model

1 Introduction

In light of global climate change, all nations are grappling with the substantial challenge of reducing greenhouse gas emissions. As of 2023, China has released 12.05 billion tons of carbon, making up 32.22% of the global CO_2 emissions total[1]. As the globe's top carbon contributor, China's ability to effectively balance economic expansion with environmental conservation is crucial to its sustainability and has far-reaching effects on global climate management. In this context, the high-tech and environmentally-friendly producer services sector is emerging as a significant player. In the "Eleventh Five-Year Plan" (2006–2010), the Chinese government first proposed expanding the producer services sector, refining and

1 Data sourced from the *CO_2 Emissions in 2023* published by the International Energy Agency (IEA).

deepening the specialization of labor, and improving the efficiency of resource allocation. Since then, producer services have seen rapid growth and increased agglomeration. However, the relationship between the agglomeration of producer services (PSA) and urban carbon emissions remains unclear. This ambiguity gives rise to the central research question of this study: How does the PSA influence urban carbon emissions?

The producer services sector, spearheaded by industries such as finance, information services, and technology services, was spun off from manufacturing. Compared to traditional energy-intensive manufacturing, producer services generally require fewer physical inputs in their operations, leading to lower energy consumption and waste production. This sector is seen as greener due to its more sustainable practices. With the restructuring of China's economy, the producer services have seen rapid growth, forming extensive agglomerations in the developed regions of eastern China and the national central cities. These conglomerates not only spark regional economic growth but also influence urban energy consumption patterns and the trajectories of carbon emissions.

PSA produces a series of environmental effects. While industrial agglomeration can promote resource efficiency through economies of scale, encouraging knowledge sharing, and aiding in the establishment and implementation of green technologies (Lan et al., 2021; Fan et al., 2023; Du and Zhang, 2023), it can also augment energy requirements (Zhao et al., 2021; Wu J. et al., 2021). Furthermore, the conglomeration of the service sector could intensify urbanization, leading to increased traffic congestion, real estate development, and lifestyle changes, all of which could significantly impact a city's carbon emissions. Understanding the link between PSA and urban carbon emissions is vital for stimulating the growth of the producer services sector and for encouraging the establishment of green, low-carbon production and lifestyle habits.

This study empirically explores the research question by examining the influence of PSA on urban carbon emissions using spatial models. It evaluates the influence mechanism of PSA and examines the heterogeneity of its impact on carbon emissions. Through these endeavors, the paper seeks to assist China in enhancing the quality of PSA, crafting differentiated carbon reduction policies, and providing insights and guidance for achieving low-carbon development goals both in China and globally.

The structure of this research is organized for clarity and progression. Section 2 presents a literature review, setting the stage for the theoretical framework discussed in Section 3. Section 4 introduces the econometric model and describes the dataset used for analysis. Section 5 delves into the results, interpreting the estimations. Finally, Section 6 concludes the study, highlighting key findings and their policy relevance.

2 Literature review

Prior studies have expounded on how elements such as urban development (Wang et al., 2021; Xiao et al., 2023), trade liberalization (Dou et al., 2021; Wang et al., 2024), environmental policy (Chen and Lin, 2021; Dong et al., 2022b), technological innovation (Suki et al., 2022; Dong et al., 2022), energy efficiency optimization (Mahapatra and Irfan, 2021; Li et al., 2022a), and industrial restructuring (Wu et al., 2021b; Zhao et al., 2022) can substantially impact regional carbon emissions. The correlation between industrial agglomeration and carbon emissions has been a common theme in research investigating the environmental impacts of industrial structuring, yet a definitive conclusion has not been reached. Much of the research posits that industrial agglomeration facilitates a decrease in carbon emissions through improved research and development (R&D), knowledge transfer and spillover effects (Yu et al., 2018; Lan et al., 2021). Conversely, some studies suggest that the growth of production scale caused by industrial concentration could expedite resource usage, thereby potentially contributing to a rise in carbon emissions (Wu et al., 2021a). The final impact may well depend on the equilibrium between these advantageous and disadvantageous effects, which implies a nonlinear relationship (He et al., 2019).

Producer services emerged from the manufacturing sector, later evolving and separating due to the outsourcing of non-essential functions by manufacturing industries. Research on PSA, an important form of industry agglomeration, has mainly focused on two aspects: its synergistic relationship with the manufacturing sector (Gao et al., 2020; Zeng et al., 2021; Xu et al., 2023; Yang and Shen, 2023) and its contributions to sustainable development (Li W. et al., 2022; Du and Zhang, 2023). Although some studies consider the impact of PSA on carbon emissions, these largely revolve around the manufacturing sector. For example, Jin et al. (2022) and Liu et al. (2022) illustrated how the carbon intensity and efficiency of the manufacturing industry can be improved by the advancement and agglomeration of producer services, respectively. Other research explores the impacts of the co-agglomeration of manufacturing and producer services on carbon emissions, but the findings have been inconsistent. Xiao et al. (2024) argue that this co-agglomeration leads to an improvement in carbon emission efficiency, while other studies suggest a nonlinear relationship (Xu et al., 2023; Meng and Xu, 2022).

So far, the direct impact of PSA on the environment remains underexplored. Only a few studies have addressed this issue. Zhao et al. (2021) reported that PSA might increase carbon emissions by promoting economic scale. Fang et al. (2022) investigated the factors influencing urban carbon emission efficiency, revealing that PSA could boost local carbon emissions efficiency and also enhance the carbon efficiency in nearby regions through demonstration effects. There is a need for more comprehensive research on the ecological effect of PSA. Moreover, further examination is needed to understand how PSA impacts the environment. Past research has studied PSA's mechanisms, focusing on its scale, technology, composition, and demonstration effects (Zhao et al., 2021; Liu et al., 2022; Fanget al., 2022). Some study examined its relationship with industrial structures, indicating that modernization of this structure could help improve urban carbon productivity (Xu et al., 2023). Sun and Li (2022) found that PSA decreases technical efficiency locally, while this negative effect could be reduced by improving industrial structure. Still, the impact of PSA on carbon emissions through energy efficiency has not been fully explored. Additionally, exiting research is insufficient in examining the endogeneity between PSA and carbon emissions. Studies typically focus on how the supply of producer services affects city-level emissions. However, the correlation could also be reversed. Areas with high carbon emissions could suffer environmental degradation and resultant diminishing standards of living. This scenario may cause a migration of skills and businesses elsewhere, thus inhibiting the accumulation of the producer service sector. In contrast, if a city is burdened with elevated carbon emission levels, the government could incentivize the congregation of service industry businesses through tax benefits, financial aid, or infrastructural investment. These strategies could potentially reduce total carbon emissions. In these instances, a misleading link between PSA and carbon emissions might be discerned. Current literature aims to counter this issue of reverse causality by introducing a 1-year lag for PSA (Liu et al., 2022). However, forecasts of the forthcoming year's emissions could influence government policies and workforce behavior within the current year. Consequently, the effectiveness of using lagged terms may not be particularly strong.

This paper aims to address the recognized lacunae in current research, offering several potential contributions. First, it introduces a fresh viewpoint. The productive service industry is characterized by high added value, high knowledge content, and a relatively low environmental impact. The emergence of PSA not only provides support and services to the manufacturing sector, enhancing its efficiency, but can also generate positive externalities that extend beyond their direct contributions to manufacturing. This work goes beyond the confines of manufacturing to directly assess how PSA influences urban carbon emissions. The findings indicate that PSA substantially lessens the carbon emission intensity in urban areas. Since direct carbon emissions in urban areas contribute to 85% of China's overall carbon emissions (Shan et al., 2019), this work offers a novel perspective for formulating carbon reduction strategies in cities. Second, the paper analyzes the methods by which PSA aids in reducing urban carbon emissions from a novel perspective. It employs the SBM-DEA method to calculate the total-factor energy efficiency and productivity of cities. The results show that PSA contributes to carbon emission reductions by enhancing total-factor energy efficiency. This discovery extends the scope of existing academic discussions. Lastly, the study introduces a novel method to circumvent the endogeneity issues often seen in industrial agglomeration and emission studies. It uses the relief amplitude of various Chinese cities as an instrumental variable for PSA. Relief amplitude is sufficiently exogenous as an instrumental variable and does not directly impact urban carbon emissions intensity, thus providing a robust tool for the analysis.

3 Theoretical analysis

3.1 PSA and energy efficiency improvement

Recent research underscores the importance of energy efficiency in lowering emissions (Akram et al., 2020; He et al., 2021). Dense production and living arrangements can lead to more centralized energy usage, resulting in lower per-unit-area energy consumption (Glaeser and Kahn, 2010). Proque et al. (2020) and Fan et al. (2023) also found that, compared to dispersed production, concentrated production methods benefit from economies of scale, aiding in the reduction of energy use. In the context of PSA, the strategic consolidation of public infrastructure has led to a marked reduction in resource idleness and wastage, which are often a consequence of the geographical dispersion of enterprises. Specifically, the centralized layout of production facilities has reduced energy loss for lighting and heating, thus cutting unnecessary energy consumption. The geographic concentration of employees allows public transportation systems to operate on a larger scale, enhancing operational efficiency and reducing the energy required for commuting. Meanwhile, the shared mechanism of information technology resources effectively prevents redundant labor and resource waste during the R&D process, thereby not only saving on R&D costs but also accelerating the speed of innovation. These shared mechanisms reduce the resource consumption for producing the same quantity of products or services, improve overall energy efficiency, and propose a novel economic development model that emphasizes energy conservation and consumption reduction.

Moreover, the enhancement of energy efficiency heavily relies on advancements in technology (Li and Lin, 2018; Chen and Liu, 2021). Producer services are characterized as talent-intensive, knowledge-intensive, and technology-intensive, which contributes significantly to energy efficiency. Marshall and Guillebaud (1961) found that in areas with a high density of producer services, innovative resources are more concentrated, and the pace of technological advancement is quicker. Furthermore, knowledge-intensive enterprises are more likely to gain the advantage of technology spillovers in an agglomerated environment (Glaeser, 1999). PSA provides geographical convenience, allowing advanced energy-saving and emission-reduction measures to spread through spillover effects, thereby improving labor productivity and energy efficiency on a broader scale. Additionally, the production efficiency of input factors varies across different sectors, and this efficiency difference causes factor flows, with energy factors tending to shift from low-efficiency sectors to high-efficiency sectors. In this process, producer services can propel a comprehensive enhancement of energy efficiency within the agglomeration area.

Hypothesis 1. PSA reduces carbon emission intensity through enhancing energy efficiency.

3.2 PSA and industrial structure adjustment

The adjustment of industrial structure can shift away from an extensive development model, which is favorable for decreasing carbon emissions (Zhao et al., 2022; Zhu, 2022). The agglomeration of producer services is a result of the deepening social division of labor and economic structural adjustment, and the agglomeration will further promote the specialization of producer services, thereby facilitating the enhancement of the overall industrial framework. In economic activities, a significant portion of information is "non-standardized," requiring effective transmission through face-to-face communication among professionals. PSA strengthens the sharing and accumulation of such "non-standardized information" in human capital (Grubel and Walker, 1989). This accumulation of professional talent, in turn, can enhance regional innovation and management capabilities, promoting the refinement of industrial structure (Cai and Xu, 2017). Furthermore, the agglomeration of producer services increases competition among firms. To capture market share, homogeneous producer service enterprises may reduce prices, which compels them to boost productivity. On the other hand, heterogeneous producer service enterprises are more likely to seek competitive advantages by enhancing technology, improving service quality, and introducing innovative products. This progression encourages the producer services industry to climb from low-end to high-end offerings, ultimately advancing the regional industrial structure.

Hypothesis 2. PSA reduces carbon emission intensity by enhancing the industrial structure.

4 Methods and data

4.1 Model specification

In this section, the study further explores how PSA impacts urban carbon emission intensity through empirical analysis. Influenced by natural conditions, geographic location, industrial transfer and technological spillover, emissions from different regions cannot be spatially isolated. Neglecting spatial correlation when studying regional carbon emissions may lead to inconsistencies between estimated and actual values. To address this, spatial models are utilized. Popular spatial models include the Spatial Lag Model (SAR), the Spatial Error Model (SEM), and the Spatial Durbin Model (SDM). Anselin et al. (2013) suggest that the SAR should be chosen when spatial dependence is a significant factor among variables, and the SEM should be selected when the error term is spatially correlated. The SDM, as detailed by Lesage and Pace (2009), is capable of handling both spatial lag and spatial error concurrently, with the SAR and SEM being its simplified variants. In the subsequent analysis, both the Likelihood Ratio (LR) test and the Wald test indicate that the SDM utilized in this study cannot be reduced to either the SEM or the SAR. Therefore, the SDM is selected for empirical analysis, and the model is constructed as follows:

$$\ln CEI_{it} = \rho \sum_{j=1, j\neq i}^{N} W_{ij} \ln CEI_{jt} + \beta \ln PSA_{it} + \gamma \sum_{j=1, j\neq i}^{N} W_{ij} \ln PSA_{jt} + \theta X_{it} + u_i + v_t + \varepsilon_{it} \tag{1}$$

where, $\ln CEI_{it}$, $\ln PSA_{it}$ are the carbon emission intensity and producer services agglomeration for city i in year t, respectively. ρ is the spatial lag coefficient. X_{it} is the set of control variables. u_i, v_t, ε_{it} are individual effect, time effect, and disturbance term, respectively. W_{ij} is the spatial weight matrix and takes the form of:

$$W_{ij} = \begin{cases} e^{-\alpha d_{ij}}, i \neq j \\ 0, i = j \end{cases} \tag{2}$$

Here, d_{ij} is the geographic distance between spatial unit i and spatial unit j. α is a coefficient that takes the reciprocal of the shortest distance between cities.

TABLE 1 Descriptive statistics of variables.

Variable	Obs	Mean	Std	Min	Max
lnCEI	3,598	−0.965	0.725	−3.522	1.748
lnPSA	3,598	−0.214	0.340	−2.128	0.684
lnTE	3,598	−1.122	0.504	−2.657	0.365
lnHD	3,598	0.047	0.096	0.000	2.152
lnSR	3,598	−0.472	1.379	−5.644	4.750
lnHUM	3,598	4.584	1.170	−5.493	7.178
lnINV	3,598	−0.439	0.460	−3.833	0.879
lnFDI	3,598	−4.627	1.392	−17.645	−1.391
lnpGDP	3,598	1.234	0.693	−0.962	3.452
lnFD	3,598	0.701	0.426	−0.580	3.059
lnER	3,598	−1.100	0.439	−4.009	0.032

4.2 Data sources and variable selection

The sample period for this paper is from 2006 to 2019, and the subjects of the study are prefecture-level cities and above[2]. After excluding cities with significant data missing and those with fewer than 100,000 employees, a balanced panel data set comprising 257 cities over 14 years was selected as the analysis sample. All data are sourced from the *China City Statistical Yearbook* of the corresponding years. The following elucidates the choice of variables and the techniques employed to build the indices. Descriptive statistics for these variables are displayed in Table 1.

4.2.1 Dependent variable

Carbon Emission Intensity (CEI). To eliminate the impact of regional economic scale, the CEI for each region is calculated by dividing the total carbon emissions of each city within a specific year by its corresponding GDP. The GDP data used in these calculations is adjusted to constant prices, using 2006 as the base year, to account for inflation. Since urban carbon emissions mainly arise from energy consumption, this study follows the methodology of Wu and Guo (2016), computing urban carbon emissions by estimating and aggregating the emissions produced from four energy sources: electricity, heat, natural gas, and liquefied petroleum gas. The calculation formula is represented as:

$$CO_2 = \sum C_{ij} = \sum E_{ij} \times f_j \tag{3}$$

In Equation 3, C_{ij} is the carbon emissions resulting from the consumption of energy j in city i, E_{ij} is the consumption quantity of energy j in city i, and f_j is the carbon emission coefficient of energy j.

2 The *China City Statistical Yearbook* stopped releasing employment figures categorized by industry after 2019. Therefore, given the research requirements and the constraints of data availability, the sample period is set from 2006 to 2019.

4.2.2 Core explanatory variable

The level of producer services agglomeration (PSA). The primary methods for measuring the degree of PSA include location entropy, the Herfindahl index, and the spatial Gini coefficient. Compared to other methods, location entropy adjusts for the impact of regional scale differences, thereby more accurately reflecting the spatial distribution within smaller areas. Consequently, location entropy is used to measure PSA in this study. Following Fang and Zhao (2021), the producer services are categorized into seven sectors,[3] and the number of individuals employed in these sectors is used as the basic indicator[4].

$$PSA_i = \left(E_{ij}\Big/\sum_j E_{ij}\right)\Big/\left(\sum_i E_{ij}\Big/\sum_i\sum_j E_{ij}\right) \tag{4}$$

In Equation 4, E_{ij}, $\sum_j E_{ij}$ represent the employment in producer service sectors and the total employment in city i, respectively; $\sum_i E_{ij}$, $\sum_i\sum_j E_{ij}$ represent the employment in producer service sectors and the total employment in all cities, respectively. This is a positive index, a higher value corresponds to a greater concentration of producer service sectors.

4.2.3 Mechanism variables

4.2.3.1 Total-factor energy efficiency (TE)

This is estimated using the SBM-DEA model that includes undesired outputs. Specifically, an optimal frontier is established using a non-parametric method. This frontier represents the most efficient production possibility based on the given inputs and outputs. The actual performance of each Decision Making Unit (DMU) is then compared against this optimal frontier to determine its relative efficiency. Assuming there are m DMUs, each of them consumes n inputs, produces u desired outputs, and v undesired outputs. The corresponding vectors are $X = (x_{ij}) \in R^+_{n\times m}$, $Y^g = (y^g_{ij}) \in R^+_{u\times m}$, $Y^b = (y^b_{ij}) \in R^+_{v\times m}$. Then the set of production possibilities can be articulated according to Equation 5:

$$P(x) = \left\{ \left(x, y^g, y^b\right) \middle| x \ge X\lambda, y^g \le Y^g\lambda, y^b = Y^b\lambda, \sum_{i=1}^{m}\lambda = 0, \lambda \ge 0 \right\} \tag{5}$$

Where λ is the weight of each cross-sectional observation. For a specific DMU, the efficiency score θ^* is obtained by solving the following linear programming problem:

$$\theta^* = \min \frac{1 - \frac{1}{n}\sum_{i=1}^{n} s_i^- \Big/ x_{i0}}{1 + \frac{1}{u+v}\left(\sum_{j=1}^{u} s_j^g \Big/ y_{j0}^g + \sum_{j=1}^{v} s_j^b \Big/ y_{j0}^b\right)} \tag{6}$$

$$s.t.\ x_0 = X\lambda + s^-, y_0^g = Y^g\lambda - s^g, y_0^b = Y^b\lambda + s^b, \lambda, s^-, s^g, s^b \ge 0$$

Where s^-, s^b and s^g are the slack variables of inputs, undesirable outputs and desirable outputs, respectively. In this article, each city is considered as a DMU, and the input indicators used include labor input, capital input, and energy input. Labor input is represented by the count of individuals employed in each city; capital input is estimated using the perpetual inventory method with 2006 as the base year; energy input is calculated using the night light simulation index. The expected output is the constant-price GDP of each city, again with 2006 as the reference year; whereas the unexpected outputs are SO_2 and CO_2 emissions. Given these assumptions, Equation 6 is solved to obtain θ^*, which is the total-factor energy efficiency.

4.2.3.2 Industrial structure rationalization index (SR)

Han et al. (2017) measured the rationality of the industrial structure based on structural deviation and the proportion of output from various industries. The formula is as follows:

$$IS = \sum_{j=1}^{3}\left(\frac{Y_j}{Y}\right)\left|\left(\frac{Y_j}{L_j}\right)\Big/\left(\frac{Y}{L}\right) - 1\right| \tag{7}$$

In Equation 7, Y is output, L is labor input, j is the industry (j = 1,2,3). When the productivity levels of all sectors are the same, that is, $Y_j/L_j = Y/L$, the economy is in a state of equilibrium, and the level of industrial structure rationalization is at its highest; at this point, IS = 0. Conversely, the further the economy deviates from the state of equilibrium, the less rational the industrial structure becomes, and the greater the value of IS.

As IS is an inverse indicator, a higher value of IS indicates a lower degree of industrial structure rationalization. In this paper, we take the reciprocal of IS, which makes the explanation of the empirical results in the subsequent text more convenient. The index is constructed according to Equation 8:

$$SR = 1\Big/IS = 1\Big/\left(\sum_{j=1}^{3}\left(\frac{Y_j}{Y}\right)\left|\left(\frac{Y_j}{L_j}\right)\Big/\left(\frac{Y}{L}\right) - 1\right|\right) \tag{8}$$

4.2.3.3 Industrial structure adjustment magnitude (HD)

Following Findeisen and Südekum (2008), it is calculated by the intensity of the re-allocation of employed personnel among industries. The calculation process is as follows:

$$HD_{it} = \left\{\left[\sum_{j=1}^{n}\left|e_i(j,t+1) - e_i(j,t)\right|\right] - \left|e_i(t+1) - e_i(t)\right|\right\}\Big/ e_i(t) \tag{9}$$

In Equation 9, $e_i(j,t+1)$, $e_i(j,t)$ represent the number of employees in industry j in city i at time $t+1$ and t, respectively. $e_i(t+1)$, $e_i(t)$ are the total number of employees in city i at time $t+1$ and t, respectively. This index is a positive indicator.

3 The seven producer service sectors are: transportation, warehousing and postal services; information transmission, computer services and software industry; financial industry; rental and business services industry; scientific research, technology services and geological exploration industry; wholesale and retail industry; water conservancy, environmental and public facilities management.

4 Given producer service sectors are mainly concentrated in municipal districts, this study is based on persons employed in municipal districts rather than the entire city.

TABLE 2 Results of Moran's I test for China's urban carbon intensity, 2006–2019.

Year	Moran's I	Z-Statistic	Year	Moran's I	Z-Statistic
2006	0.178***	4.536	2013	0.221***	5.626
2007	0.176***	4.496	2014	0.188***	4.802
2008	0.186***	4.749	2015	0.252***	6.392
2009	0.198***	5.050	2016	0.259***	6.571
2010	0.210***	5.343	2017	0.241***	6.125
2011	0.192***	4.894	2018	0.255***	6.470
2012	0.198***	5.058	2019	0.214***	5.444

Note: 1) Prepared based on the processing results from STATA 16 software. 2) $*p < 0.1$. $**p < 0.05$. $***p < 0.01$.

4.2.4 Control variables

(1) Human Capital (HUM) facilitates the dissemination of knowledge and the generation of innovative ideas. The creation of advanced technologies can reduce energy consumption by increasing production efficiency, thereby reducing carbon emissions. Therefore, HUM is used as a control variable and quantified by the ratio of university students per 10,000 individuals.
(2) Physical Capital Investment (INV) not only expands the economic scale but also increases energy consumption, thereby affecting carbon emission intensity. Hence, this indicator is introduced as a control variable and is gauged by the ratio of fixed asset investment to GDP.
(3) Foreign Direct Investment (FDI) is determined by its proportion in relation to GDP. The impact of FDI on carbon emission intensity is complex. On one hand, FDI can stimulate regional economic growth, potentially increasing energy consumption and carbon emissions. On the other hand, FDI can lead to technology spillovers, promoting the optimization of regional industrial structures, potentially reducing carbon emissions.
(4) Economic Development (pGDP), a significant driver of carbon emissions, is included as a control variable and quantified by *per capita* GDP.
(5) Financial Development (FD) has a dual effect on carbon emissions. It can increase carbon emissions by stimulating demand and energy consumption. Simultaneously, it can reduce emissions by facilitating structural adjustments and promoting cleaner production methods. Hence, it is set as a control variable and measured by the ratio of year-end balances of loans and deposits in financial institutions to GDP.
(6) Environmental Regulation (ER) reflects the commitment of local governments to sustainable development and can influence regional carbon emission behaviors. ER is calculated by using Python to tally the occurrence of environmentally related terms in the annual reports of provincial governments. The resulting figure is then adjusted by the output value share of secondary industries in each city within the province for that year.

5 Empirical results and analysis

5.1 Spatial correlation test

Prior to utilizing the spatial econometric approach, it is crucial to initially examine the spatial correlation of the dependent variable. Currently, the most widely used test for this purpose is Moran's I.

$$I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\left(x_i - \bar{x}\right)\left(x_j - \bar{x}\right)}{S^2\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \tag{10}$$

In Equation 10, S^2 is the sample variance, w_{ij} is the spatial weight matrix. Moran's I values range from −1 to 1, with the magnitude indicating the strength of the spatial correlation of the variable in question. According to the results presented in Table 2, the Moran's I values for the intensity of carbon emissions in Chinese cities from 2006 to 2019 are all positive and highly significant, with a noticeable rise in spatial dependence. This means that cities exhibiting high carbon emission intensity are typically neighbored by regions with comparable emission levels. Conversely, cities with low emission intensity are typically near regions with low emissions as well. This pattern of spatial correlation signifies the appropriateness of employing a spatial model.

5.2 Regression results and analysis

To identify the most suitable estimation form of the spatial model, the Lagrange Multiplier (LM) test, the Likelihood Ratio (LR) test, the Wald test, and the Hausman test are conducted sequentially on Equation 2, following the methodology proposed by Elhorst (2014). The findings reveal that both the LM-lag and LM-error are statistically significant at the 1% level, suggesting a preference for the spatial model over the OLS model. Moreover, the LR and Wald tests provide strong evidence against simplifying the SDM to either the SAR or SEM. Additionally, the Hausman test favors fixed effects over random effects. Consequently, a two-way fixed effects SDM is used for analysis. Results from the OLS, SAR, and SEM models are also presented for comparison.

Table 3 shows that the coefficients of PSA are always negative across various models and are statistically significant at the 1% level.

TABLE 3 Baseline results.

	OLS	SAR	SEM	SDM	SDM [Wx]
lnPSA	−0.1406**	−0.1383***	−0.1398***	−0.1468***	0.0096
	(−2.33)	(−5.31)	(−5.33)	(−5.61)	(0.18)
lnHUM	−0.0304	−0.0272*	−0.0242*	−0.0239*	−0.0772***
	(−0.85)	(−1.92)	(−1.70)	(−1.70)	(−2.91)
lnINV	−0.1173***	−0.1125***	−0.1193***	−0.1144***	0.0308
	(−2.91)	(−7.50)	(−7.63)	(−6.65)	(1.22)
lnFDI	0.0046	0.0055	0.0069	0.0115*	−0.0263***
	(0.35)	(0.96)	(1.18)	(1.88)	(-2.76)
lnpGDP	0.0486	0.0703*	0.0884**	0.1981***	−0.4439***
	(0.49)	(1.66)	(1.99)	(4.04)	(-5.79)
lnFD	0.0897	0.1039***	0.1274***	0.1674***	−0.4104***
	(0.84)	(2.58)	(3.06)	(3.95)	(−5.84)
lnER	−0.0574*	−0.0517***	−0.0548***	−0.0232	−0.0326
	(−1.93)	(−2.88)	(−2.80)	(−0.77)	(−0.85)
$\lambda or \rho$		0.1315***	0.1372***		0.1140***
		(5.50)	(5.60)		(4.71)
Time fixed	Y	Y	Y		Y
City fixed	Y	Y	Y		Y
N	3,598	3,598	3,598		3,598

Note: t-statistics are presented in parentheses. *p < 0.1; **p < 0.05; ***p < 0.01. This notation applies to all subsequent tables as well.

This suggests that when producer services cluster together, they create beneficial external effects that significantly lower carbon emission intensity in urban areas. Moreover, the spatial lag coefficient ρ is significantly positive, implying a positive spatial correlation or interdependence of carbon emissions among cities in China. This observation underscores the importance of regional collaboration in addressing environmental issues. Further, Wx × lnPSA coefficient is not significant, suggesting that the local development of PSA has minimal influence on carbon emission reduction in adjacent regions. A possible explanation is that China's productive service clusters are predominantly led by government policies, rather than market forces. This approach has somewhat affected the clusters' competitiveness, has not effectively facilitated the exchange of talent, knowledge, and technology, and has thus weakened the positive effects on carbon emissions in neighboring areas.

Regarding the control variables, the inhibitory effects of increased human capital and physical capital on carbon emissions are significantly positive. This may be because skilled individuals and environment-friendly investments contribute to cleaner production, which, in turn, promotes regional decarbonization and sustainable development. Foreign direct investment, economic development, and financial development significantly increase local carbon emission intensity while reducing that of neighboring regions. This could be because the substantial inflow of foreign capital, accelerated economic growth, and rapid financial expansion collectively consume a large amount of natural resources, thus negatively impacting the local ecological environment. However, foreign capital and economic development can bring advanced knowledge and technology, which may spread to neighboring regions, resulting in a decrease in the carbon emission intensity of these areas. Environmental regulations may reduce urban carbon emissions by compelling businesses to use clean energy sources, adopt emission reduction technologies, and by raising public awareness of low carbon practices. The environmental regulation coefficient is not statistically meaningful, potentially due to the diverse intensity of environmental regulation enforcement across various cities.

5.3 Robustness test

To confirm the solidity of the aforementioned analysis, the subsequent methods were employed: (1) Replacing the spatial weight matrix. Since connections between spatial units may be influenced by not only geographic distances but also by regional economic activity, a combined weighting matrix incorporating geographic location and economic linkages is constructed. Equation 1 is then re-estimated. The matrix is in the form of $W_{ij}^{e} = (\overline{Y_i} \times \overline{Y_j})/d_{ij}^{2}$, with diagonal elements taking 0. Where $\overline{Y_i}$ and $\overline{Y_j}$ are average values of GDP *per capita* for city i and j, respectively, during the observation period. (2) Altering the core

TABLE 4 Robustness of baseline results.

	(1)	(2)	(3)	(4)	(5)	(6)
lnPSA	−0.1384***	−0.1086***	−0.1438***	−0.1154***	−0.1403***	−0.0349*
	(-5.32)	(−4.78)	(−5.54)	(−4.19)	(−5.10)	(−1.94)
ρ	0.1525***	0.1108***	0.1076***	0.1114***		0.0534***
	(4.01)	(4.57)	(4.38)	(4.38)		(2.71)
Controls	Y	Y	Y	Y	Y	Y
Time fixed	Y	Y	Y	Y	Y	Y
City fixed	Y	Y	Y	Y	Y	Y
N	3,598	3,598	3,598	3,341	3,598	3,341

independent variable. Narrowing the scope of producer services, and the main regression model is then retested[5]. (3) Changing the dependent variable. Urban carbon emission intensity is recalculated as *per capita* carbon emissions, and the main regression model is reapplied. The outcomes of the robustness tests are presented in the initial three columns of Table 4, demonstrating that the impact of PSA on urban carbon emission intensity is consistent with the findings from the primary model.

To relieve the potential issues of reverse causality and omitted variables between PSA and carbon emissions intensity, the following methods are used for endogeneity testing: 1) First-order lag of PSA. While the likelihood of reverse causality—where urban carbon emission intensity affects the PSA—is relatively low, it is crucial to note that elevated carbon emission intensity could negatively impact the inflow of talent, capital, and technology into urban areas. This effect, often referred to as the crowding-out effect, could subsequently influence the degree of PSA. To mitigate potential bidirectional causation issues, this study substitutes PSA with its first-order lagged value and retest the main model. 2) Instrumental variable method. This method uses relief amplitude as an instrumental variable for PSA. Relief amplitude is a crucial factor in urban construction, as areas with significant relief are unsuitable for housing and CBD development. Underdeveloped CBDs and public service infrastructures can further hinder the clustering of high-tech industries. Moreover, relief amplitude is sufficiently exogenous to serve as an instrumental variable and does not directly impact urban carbon emissions intensity. 3) A dynamic SDM. The dynamic panel model includes the core dependent variable's value from the previous period as a regressor. Since the lagged dependent variable captures the influence of unaccounted variables, accounting for it mitigates the bias due to omitted variables to a certain degree. The regression outcomes, detailed in the final three columns of Table 4, illustrate that after addressing a range of endogeneity issues, PSA continues to be a significant element in diminishing urban carbon emission intensity.

5.4 Heterogeneity test

The above empirical analysis shows that PSA can notably reduce the intensity of urban carbon emissions. However, it is crucial to acknowledge that cities in China vary in size and do not follow the same development path. To account for these differences, the following heterogeneity tests are conducted.

5.4.1 Variations in resource dependency

China is a vast country with diverse resource endowments across regions, and the developmental paths of cities rich in resources differ significantly from those lacking them. In line with the classification provided by the *National Sustainable Development Plan for Resource Cities (2013–2020)*, this study categorizes the sample of 257 cities into 99 resource-based and 158 non-resource-based cities. Table 5 reveals that in non-resource-based cities, PSA notably reduces carbon emission intensity. However, this positive effect is not as prominent in resource-based cities. This difference can be attributed to two factors. First, resource-based cities are less constrained by natural resources, resulting in insufficient motivation to improve energy efficiency. Second, resource-rich areas tend to develop resource-intensive industries and have formed path dependence, resulting in low efficiency of structural adjustment. These two factors together impede the carbon reduction process in resource-based cities.

5.4.2 Variations in city size

The impact of PSA varies with the size of the city. Following the *Notice on Adjustment of City Size Classification Criteria* issued by the State Council in 2014, sample cities are divided into four groups based on the number of permanent residents within each city's municipal district at the end of the year. These groups include large cities I (with populations of 3 million and above), large cities II (with populations ranging from 1 million to 3 million), medium-sized cities (with populations between 5,00,000 and 1 million), and small cities (with populations of 5,00,000 and below).

As depicted in Table 5, PSA can substantially decrease the carbon emission intensity in medium and large cities. Conversely, it appears to increase the same in small cities. This discrepancy may

5 Only five producer service sectors are considered here, they are: transportation, warehousing and postal services; information transmission, computer services and software industry; financial industry; rental and business services industry; scientific research, technology services and geological exploration industry.

TABLE 5 Heterogeneous impacts.

	Resource-based city		City size			
	Yes	No	Small cities	Medium-sized cities	Large cities II	Large cities I
lnPSA	−0.0365	−0.1901***	0.1667**	−0.1408***	−0.2101***	−0.1102*
	(−0.87)	(−5.76)	(2.01)	(−2.66)	(−5.77)	(−1.91)
ρ	0.0605**	0.0419	0.0599	0.0770**	0.1948***	0.1042**
	(1.98)	(1.56)	(1.31)	(2.46)	(6.87)	(2.03)
Controls	Y	Y	Y	Y	Y	Y
Time fixed	Y	Y	Y	Y	Y	Y
City fixed	Y	Y	Y	Y	Y	Y
N	1,386	2,212	336	1,050	1708	504

be due to the insufficient market size in small cities, which prevents the formation of a "clustering effect." Additionally, small cities often suffer from duplicated construction and low-level infrastructure development. This results in resource misallocation and efficiency distortion, which in turn increases the carbon emission intensity. As a city expands in size, the total demand for producer services also increases. As a result, PSA exerts a more significant influence in curbing carbon emissions. It's important to highlight that in large cities I, the advantageous impact of PSA has lessened. Gao and Yuan (2020) argue that this is because the agglomeration of inefficient and homogeneous producer service enterprises in mega-cities leads to resource congestion and energy waste, which ultimately undermines the effectiveness of carbon emission reduction efforts.

TABLE 6 Results of the mechanism test for energy efficiency.

	lnTE	lnSE	lnEC
lnPSA	0.0815***	−0.0854**	0.0455**
	(3.92)	(−2.46)	(2.22)
ρ	0.2721***	0.0918***	0.2245***
	(12.72)	(3.83)	(10.17)
Controls	Y	Y	Y
Time fixed	Y	Y	Y
City fixed	Y	Y	Y
N	3,598	3,598	3,598

5.5 Mechanism test

5.5.1 Energy efficiency improvement

PSA actively promotes the sharing of knowledge and the spread of technology, encouraging regions to adopt cleaner production technologies to optimize their energy use. Moreover, the centralized production approach leads to economies of scale, which, in turn, reduce the resource input required for each unit of output, consequently enhancing regional energy efficiency. Heterogeneity analysis demonstrates that PSA's effect on curbing carbon emissions is more pronounced in cities that do not rely on natural resources. The mechanism of energy efficiency is probably a crucial factor in this observed phenomenon.

The significant role of energy efficiency in influencing carbon emission levels is underscored. To this end, Table 6 offers a detailed regression analysis that isolates and examines the impact of PSA on energy efficiency. Column 1) reveals the impact of PSA on total-factor energy efficiency. The coefficient of PSA indicates that a 1% increase in PSA can enhance total-factor energy efficiency by 0.0815%. In Column 2), single-factor energy efficiency is examined in place of total-factor energy efficiency. This measure of energy efficiency is quantified by the amount of standard coal consumed per unit of GDP, commonly referred to as energy intensity (SE). The results indicate that with a 1% rise in PSA, the energy input per unit of output decreases by 0.0854%. Furthermore, the SMB-GML method is employed to calculate the green total factor productivity (GTFP) of each city. This measurement employs the same inputs and outputs as those used in the assessment of total-factor energy efficiency. GTFP is then decomposed into technical progress (TC) and technical efficiency (EC). Technical efficiency (EC) reflects changes in efficiency resulting from alterations in management, technology, production scale, and other factors, providing a comprehensive assessment of resource efficiency. Technical efficiency (EC) is regressed in Column 3), and the conclusions remain consistent. This implies that PSA can effectively enhance energy efficiency, thus Hypothesis 1 is verified.

5.5.2 Industrial structure adjustment

The adjustment of industrial structure involves two aspects. Firstly, it entails the transition of the dominant industry from the primary sector to the secondary and tertiary sectors within the three major industry categories. Secondly, it involves the replacement of outdated technologies with high-tech alternatives within each industry. A significant amount of research has confirmed the beneficial effect of industrial structure modification on reducing carbon emissions. Therefore, this work reports only the effect of PSA on industrial structure adjustment.

TABLE 7 Results of the mechanism test for structural adjustment.

	lnSRt	lnSRt+1	lnHDt	lnHDt+1
lnPSA	0.2757***	0.2158***	0.0411***	0.0156*
	(5.09)	(3.70)	(4.85)	(1.68)
ρ	0.2389***	0.2262*	0.1313***	0.1391***
	(10.61)	(1.88)	(5.33)	(5.41)
Controls	Y	Y	Y	Y
Time fixed	Y	Y	Y	Y
City fixed	Y	Y	Y	Y
N	3,598	3,341	3,598	3,341

Table 7 shows that the coefficient of PSA is positive at the 1% level when the dependent variable is the industrial structure rationalization index (SR). This result remains consistent when SR is advanced by one period. This suggests that PSA helps to intensify market competition, reduce transaction costs, and promote the effective allocation of production factors within and across industries, thereby promoting the economy towards a more rational industrial structure. Meanwhile, PSA can enhance the division of labor, optimize the business environment, and attract highly skilled talent. This significantly bolsters the modernization of conventional industries and the growth of emerging industries, thereby increasing the magnitude of regional industrial restructuring. Replacing the dependent variable with the industrial structure adjustment amplitude (HD), the results indicate that with each 1% rise in PSA, the industrial structure adjustment amplitude increases by 0.0411%. This suggests that PSA can accelerate economic structure transformation. Hypothesis 2 is verified.

6 Conclusion

This study utilizes data from 257 Chinese cities between 2006 and 2019, and applies a spatial econometric model to explore how PSA impacts the intensity of urban carbon emissions. The results indicate that spatial spillover effects are crucial to understanding patterns of carbon emissions, with high-emission regions often adjacent to others with similarly high levels. PSA can significantly decrease the intensity of local carbon emissions by promoting energy efficiency and refining the industrial structure. However, the absence of effective mechanisms for skill and technology exchange between regions limits the broader impact of local PSA on surrounding area emissions. When considering variations between cities, cities rich in resources may have developed a kind of path dependence, which diminishes the mitigation effects of PSA. Meanwhile, smaller cities might suffer from the duplicated and low-level of construction, leading to an increase in carbon emission intensity. Consequently, the positive effects of PSA on reducing carbon emissions are more evident in non-resource-based cities, as well as in medium-sized and Type II large cities.

These findings yield several significant policy implications. First, there should be a focus on the regional overflow consequences of carbon emissions. Environmental governance framework should break through the restrictions of administrative boundaries, explore a collaborative approach to air pollution management across cities, and promote regional linkage for the transition to low-carbon cities. Second, market mechanisms should be adhered to as the main driver, supplemented by government policy support, to strengthen the construction of producer services clusters. Establish an educational and training cooperation network within the region, promote the circulation of expertise and technological interchange, and accelerate the promotion and application of low-carbon technologies. Third, enhance the sharing of information and infrastructure within clusters to form a scaled factor market and promote energy efficiency improvements. At the same time, optimize the quality of producer services, continuously innovate services and products, and elevate the producer services industry from low-end to high-end, promoting industrial structure optimization. Fourth, formulate differentiated low-carbon development plans according to city types. Resource-based cities can reduce their dependence on traditional resources by introducing and developing circular economies and clean energy industries. Meanwhile, large cities should control the excessive expansion of the producer services industry to avoid redundant construction, whereas medium-sized cities can accept the industrial transfer from large cities by establishing industrial parks, business centers, and other means. Small cities can develop suitable clusters for producer services by identifying their unique advantages and potential for development. For example, they can become outsourcing centers for specific service businesses or develop into professional service centers for certain industries. Such strategies can prevent the environmental negative impacts that may arise from blindly developing clusters of producer services.

It should be noted that this study has certain limitations, primarily due to the difficulty of acquiring data. The research relies chiefly on a sample of urban macro data for empirical analysis. Moreover, data concerning the number of people employed in various industries in Chinese cities post-2020 is unavailable, which may affect the timeliness and relevance of the policy implications derived from this study. Looking towards future research directions, the COVID-19 pandemic has popularized the remote work model, which could potentially change the agglomeration patterns of productive service industries, thereby indirectly affecting the intensity of urban carbon emissions. On the one hand, with the spread of remote work, employees no longer need to be in the same location to perform their jobs. This could significantly decrease the demand for commuting, potentially reducing urban traffic carbon emissions. On the other hand, remote work may increase the reliance on data centers, which could, in turn, increase their energy use and thereby elevate carbon emissions. The specific effects of these impacts may vary depending on the region and the industry. Therefore, more research is necessary to more comprehensively understand the impact of these changes on carbon emissions.

Data availability statement

Publicly available datasets were analyzed in this study. This data can be found here: China City Statistical Yearbook.

Author contributions

SZ: Writing–original draft, Writing–review and editing.

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Conflict of interest

The author declares that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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References

Akram, R., Chen, F., Khalid, F., Ye, Z., and Majeed, M. T. (2020). Heterogeneous effects of energy efficiency and renewable energy on carbon emissions: evidence from developing countries. *J. Clean. Prod.* 247, 119122. doi:10.1016/j.jclepro.2019.119122

Anselin, L., Florax, R., and Rey, S. J. (2013). *Advances in spatial econometrics: methodology, tools and applications*. New York: Springer.

Cai, H., and Xu, Y. (2017). Does trade openness affect the upgrading of China's industrial structure? *J. Quant. Tech. Econ.* 34, 3–22. doi:10.13653/j.cnki.jqte.2017.10.001

Chen, X., and Lin, B. (2021). Towards carbon neutrality by implementing carbon emissions trading scheme: policy evaluation in China. *En. Pol.* 157, 112510. doi:10.1016/j.enpol.2021.112510

Chen, Y., and Liu, Y. (2021). How biased technological progress sustainably improve the energy efficiency: an empirical research of manufacturing industry in China. *Energy* 230, 120823. doi:10.1016/j.energy.2021.120823

Dong, F., Zhu, J., Li, Y., Chen, Y., Gao, Y., Hu, M., et al. (2022a). How green technology innovation affects carbon emission efficiency: evidence from developed countries proposing carbon neutrality targets. *Environ. Sci. Pollut. Res.* 29 (24), 35780–35799. doi:10.1007/s11356-022-18581-9

Dong, Z., Xia, C., Fang, K., and Zhang, W. (2022). Effect of the carbon emissions trading policy on the co-benefits of carbon emissions reduction and air pollution control. *En. Pol.* 165, 112998. doi:10.1016/j.enpol.2022.112998

Dou, Y., Zhao, J., Malik, M. N., and Dong, K. (2021). Assessing the impact of trade openness on CO2 emissions: evidence from China-Japan-ROK FTA countries. *J. Environ. Manag.* 296, 113241. doi:10.1016/j.jenvman.2021.113241

Du, M., and Zhang, Y. J. (2023). The impact of producer services agglomeration on green economic development: evidence from 278 Chinese cities. *Energy Econ.* 106769, 106769. doi:10.1016/j.eneco.2023.106769

Elhorst, J. P. (2014). Matlab software for spatial panels. *Int. Reg. Sci. Rev.* 37 (3), 389–405. doi:10.1177/0160017612452429

Fan, F., Dai, S., Yang, B., and Ke, H. (2023). Urban density, directed technological change, and carbon intensity: an empirical study based on Chinese cities. *Technol. Soc.* 72, 102151. doi:10.1016/j.techsoc.2022.102151

Fang, G., Gao, Z., Tian, L., and Fu, M. (2022). What drives urban carbon emission efficiency? - Spatial analysis based on nighttime light data. *Appl. Energ.* 312, 118772. doi:10.1016/j.apenergy.2022.118772

Fang, H., and Zhao, S. (2021). Has the belt and road initiative promoted the upgrading of China's industrial structure? A difference-in-differences test based on 285 cities of China. *Econ. Res.* 1, 29–42. doi:10.13269/j.cnki.ier.2021.01.003

Findeisen, S., and Südekum, J. (2008). Industry churning and the evolution of cities: evidence for Germany. *J. Urban Econ.* 64 (2), 326–339. doi:10.1016/j.jue.2008.02.003

Gao, K., and Yuan, Y. (2020). Research on resource misallocation effect of producer services agglomeration from the perspective of space. *Mod. Econ. Sci.* 42 (6), 108–119.

Gao, X., Lu, C., and Mao, J. (2020). Effects of urban producer service industry agglomeration on export technological complexity of manufacturing in China. *Entropy* 22 (10), 1108. doi:10.3390/e22101108

Glaeser, E. L. (1999). Learning in cities. *J. Urban Econ.* 46 (2), 254–277. doi:10.1006/juec.1998.2121

Glaeser, E. L., and Kahn, M. E. (2010). The greenness of cities: carbon dioxide emissions and urban development. *J. Urban Econ.* 67 (3), 404–418. doi:10.1016/j.jue.2009.11.006

Grubel, H., and Walker, M. (1989). *Service industry growth: causes and effects*. London: Fraser Institute.

Han, Y., Huang, L., and Wang, X. (2017). Do industrial policies promote industrial structure upgrading? Theory and evidence from China's development-oriented local government. *Econ. Res. J.* 52 (8), 33–48.

He, W., Zhang, H., Chen, X., and Yan, J. (2019). An empirical study on population density, economic agglomeration and carbon emission state of Chinese provinces: from the perspective of agglomeration economy effects, congestion effects and spatial effects. *Nankai Econ. Stud.* 2, 207. doi:10.14116/j.nkes.2019.02.011

He, Y., Liao, N., and Lin, K. (2021). Can China's industrial sector achieve energy conservation and emission reduction goals dominated by energy efficiency enhancement? A multi-objective optimization approach. *En. Pol.* 149, 112108. doi:10.1016/j.enpol.2020.112108

Jin, Z., Li, Z., and Yang, M. (2022). Producer services development and manufacturing carbon intensity: evidence from an international perspective. *En. Pol.* 170, 113253. doi:10.1016/j.enpol.2022.113253

Lan, F., Sun, L., and Pu, W. (2021). Research on the influence of manufacturing agglomeration modes on regional carbon emission and spatial effect in China. *Econ. Model.* 96, 346–352. doi:10.1016/j.econmod.2020.03.016

LeSage, J., and Pace, R. K. (2009). *Introduction to spatial econometrics*. New York: CRC Press, Taylor and Francis Group.

Li, K., and Lin, B. (2018). How to promote energy efficiency through technological progress in China? *Energy* 143, 812–821. doi:10.1016/j.energy.2017.11.047

Li, R., Li, L., and Wang, Q. (2022a). The impact of energy efficiency on carbon emissions: evidence from the transportation sector in Chinese 30 provinces. *Sustain. Cities Soc.* 82, 103880. doi:10.1016/j.scs.2022.103880

Li, W., Zhang, Y., Yang, C., Gong, W., Wang, C., and Zhang, R. (2022b). Does producer services agglomeration improve urban green development performance of the Yangtze River Economic Belt in China? *Ecol. Indic.* 145, 109581. doi:10.1016/j.ecolind.2022.109581

Liu, X., Zhang, X., and Sun, W. (2022). Does the agglomeration of urban producer services promote carbon efficiency of manufacturing industry? *Land Use Policy* 120, 106264. doi:10.1016/j.landusepol.2022.106264

Mahapatra, B., and Irfan, M. (2021). Asymmetric impacts of energy efficiency on carbon emissions: a comparative analysis between developed and developing economies. *Energy* 227, 120485. doi:10.1016/j.energy.2021.120485

Marshall, A., and Guillebaud, C. W. (1961). *Principles of economics: an introductory volume*. London: Macmillan.

Meng, X. N., and Xu, S. C. (2022). Can industrial collaborative agglomeration reduce carbon intensity? Empirical evidence based on Chinese provincial panel data. *Environ. Sci. Pollut. Res.* 29 (40), 61012–61026. doi:10.1007/s11356-022-20191-4

Proque, A. L., dos Santos, G. F., Junior, A. A. B., and Larson, W. D. (2020). Effects of land use and transportation policies on the spatial distribution of urban energy consumption in Brazil. *Energy Econ.* 90, 104864. doi:10.1016/j.eneco.2020.104864

Shan, Y., Liu, J., Liu, Z., Shao, S., and Guan, D. (2019). An emissions-socioeconomic inventory of Chinese cities. *Sci. Data.* 6 (1), 190027. doi:10.1038/sdata.2019.27

Suki, N. M., Suki, N. M., Sharif, A., Afshan, S., and Jermsittiparsert, K. (2022). The role of technology innovation and renewable energy in reducing environmental degradation in Malaysia: a step towards sustainable environment. *Renew. Energ.* 182, 245–253. doi:10.1016/j.renene.2021.10.007

Sun, S., and Li, X. (2022). Productive services agglomeration, financial development and regional innovation efficiency in the Yangtze River Economic Zone. *FRL* 50, 103221. doi:10.1016/j.frl.2022.103221

Wang, Q., Zhang, F., and Li, R. (2024). Free trade and carbon emissions revisited: the asymmetric impacts of trade diversification and trade openness. *Sustain. Dev.* 32 (1), 876–901. doi:10.1002/sd.2703

Wang, W. Z., Liu, L. C., Liao, H., and Wei, Y. M. (2021). Impacts of urbanization on carbon emissions: an empirical analysis from OECD countries. *En. Pol.* 151, 112171. doi:10.1016/j.enpol.2021.112171

Wu, J., and Guo, Z. (2016). Research on the convergence of carbon dioxide emissions in China: a continuous dynamic distribution approach. *Stat. Res.* 33 (1), 54–60. doi:10.19343/j.cnki.11-1302/c.2016.01.008

Wu, J., Xu, H., and Tang, K. (2021a). Industrial agglomeration, CO2 emissions and regional development programs: a decomposition analysis based on 286 Chinese cities. *Energy* 225, 120239. doi:10.1016/j.energy.2021.120239

Wu, L., Sun, L., Qi, P., Ren, X., and Sun, X. (2021b). Energy endowment, industrial structure upgrading, and CO2 emissions in China: revisiting resource curse in the context of carbon emissions. *Resour. Policy.* 74, 102329. doi:10.1016/j.resourpol.2021.102329

Xiao, Y., Huang, H., Qian, X. M., Zhang, L. Y., and An, B. W. (2023). Can new-type urbanization reduce urban building carbon emissions? New evidence from China. *Sustain. Cities Soc.* 90, 104410. doi:10.1016/j.scs.2023.104410

Xiao, Y., Xu, Y., Li, M., Wang, Y., and Chen, W. (2024). Does the integration of manufacturing and producer services improve carbon emission efficiency? *Clean. Technol. Environ. Policy.* 26 (5), 1603–1619. doi:10.1007/s10098-023-02567-3

Xu, H., Liu, W., and Zhang, D. (2023). Exploring the role of co-agglomeration of manufacturing and producer services on carbon productivity: an empirical study of 282 cities in China. *J. Clean. Prod.* 399, 136674. doi:10.1016/j.jclepro.2023.136674

Yang, Z., and Shen, Y. (2023). The impact of intelligent manufacturing on industrial green total factor productivity and its multiple mechanisms. *Front. Environ. Sci.* 10. doi:10.3389/fenvs.2022.1058664

Yu, X., Chen, H., Wang, B., Wang, R., and Shan, Y. (2018). Driving forces of CO2 emissions and mitigation strategies of China's national low carbon pilot industrial parks. *Appl. Energ.* 212, 1553–1562. doi:10.1016/j.apenergy.2017.12.114

Zeng, W., Li, L., and Huang, Y. (2021). Industrial collaborative agglomeration, marketization, and green innovation: evidence from China's provincial panel data. *J. Clean. Prod.* 279, 123598. doi:10.1016/j.jclepro.2020.123598

Zhao, J., Dong, X., and Dong, K. (2021). How does producer services' agglomeration promote carbon reduction? the case of China. *Econ. Model.* 104, 105624. doi:10.1016/j.econmod.2021.105624

Zhao, J., Jiang, Q., Dong, X., Dong, K., and Jiang, H. (2022). Industrial structure adjustment and CO_2 emissions reduction: a spatial and mediation effects analysis for China. *Energy Econ.* 105, 105704. doi:10.1016/j.eneco.2021.105704

Zhu, X. (2022). Have carbon emissions been reduced due to the upgrading of industrial structure? Analysis of the mediating effect based on technological innovation. *Environ. Sci. Pollut. Res.* 29 (36), 54890–54901. doi:10.1007/s11356-022-19722-w