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RESEARCH ARTICLE

Does government intervention affect CO_2 emission reduction effect of producer service agglomeration? Empirical analysis based on spatial Durbin model and dynamic threshold model

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Abstract
Achieving carbon peak and carbon neutrality is an inherent requirement for countries to promote green recovery and transformation of the global economy after the COVID-19 pandemic. As “a smoke-free industry,” producer services agglomeration (PSA) may have significant impacts on CO_2 emission reduction. Therefore, based on the nightlight data to calculate the CO_2 emissions of 268 cities in China from 2005 to 2017, this study deeply explores the impact and transmission mechanism of PSA on CO_2 emissions by constructing dynamic spatial Durbin model and intermediary effect model. Furthermore, the dynamic threshold model is used to analyze the nonlinear characteristics between PSA and CO_2 emissions under different degrees of government intervention. The results reveal that: (1) Generally, China’s CO_2 emissions are path-dependent in the time dimension, showing a “snowball effect.” PSA significantly inhibits CO_2 emissions, but heterogeneous influences exist in different regions, time nodes, and sub-industries; (2) PSA can indirectly curb CO_2 emissions through economies of scale, technological innovation, and industrial structure upgrading. (3) The impact of PSA on China’s CO_2 emissions has an obvious double threshold effect under different degree of government intervention. Accordingly, the Chinese government should increase the support for producer services, dynamically adjust industrial policies, take a moderate intervention, and strengthen market-oriented reform to reduce CO_2 emissions. This study opens up a new path for the low-carbon economic development and environmental sustainability, and also fills in the theoretical gaps on these issues. The findings and implications will offer instructive guideline for early achieving carbon peak and carbon neutrality.

Keywords PSA · Government intervention · China’s CO_2 emissions · Spatial Durbin model · Dynamic threshold model

Introduction

As a result of the acceleration of industrialization and the combustion of fossil fuels in recent decades, a large number of greenhouse gases represented by CO_2 are emitted, resulting in global surface temperatures increasing and more frequent freak weather (Khan et al. 2019; Yan et al. 2021). Currently, the Chinese government is dedicated to carbon emission reduction. The strategic policy of “establishing and improving an economic system for green and low-carbon circular development” has been proposed at the 19th National Congress of the Communist Party of China. In the general debate of the seventy-fifth United Nations General Assembly on September 22, 2020, Chinese President Xi Jinping further claimed that the goal of “carbon peak and carbon neutrality” should be achieved before 2030 and 2060 respectively so as to scale up its Intended Nationally Determined Contributions. Nevertheless, China is proceeding deep into the

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development of urbanization and industrialization (Jiang and Lin 2012; Zhao et al. 2022), and the total carbon emissions have been on the rise. Consequently, China is confronting great pressure on carbon emission reduction (Zhang and Da 2015). Up to now, there is agreement among scholars that the most effective way to reduce carbon emissions is to facilitate the upgrading of industrial structure and drastic expansion of tertiary industry (Zhang et al. 2018; Li et al. 2019; Zhang et al. 2020a). It is further proposed at the 19th National Congress of the Communist Party of China that modern service industries should be given priority in the tertiary industry. Recently, the service industry has figured prominently in China's national economy. In 2019, the added value of the service industry increased by 6.9%, accounting for 53.9% of GDP, of which the added value of the producer service industry accounted for 60% of the service industry.[1] With the increasing proportion of the service industry in China's economic development, producer services with the trait of energy conservation and emission reduction have become a significant feature in the new era (Zhao et al. 2021a).

As an important part of the modern service industries, producer services are "smoke-free industries," which are gradually becoming the key force to promote the development of low-carbon economy (Wu et al. 2013). Statistics show that energy consumed by each unit output of the service industry is no more than 33% of the secondary industry and 40% of the primary industry (Tan et al. 2016). At present, the main problem in the traditional manufacturing industry is the neglect of energy conservation and pollution reduction (Ding et al. 2015; Yang et al. 2021b), while producer services can effectively alleviate "the stubborn diseases" of over-consumption and low output in the manufacturing industry, ultimately reducing global environmental pollution (Yang et al. 2021a). Industrial agglomeration can fuel the intensive and large-scale development of agglomeration areas. Therefore, accelerating the development of PSA is not only an important way to alleviate overcapacity and environmental constraints but also an important strategic measure to finally realize the development of green and low-carbon economy (Yang et al. 2020). However, the rapid progress of industrial agglomeration will bring about a "crowding effect" (Xi 2016). Relying too much on the market to regulate the economy may induce the disadvantages of blindness, spontaneity, and lag of such as unscientific agglomeration development structure and disgusting competition among enterprises, resulting in a series of environmental problems. Therefore, the government should adopt the appropriate regulation and effective intervention. On the border issue of government intervention, Chinese scholars Lin Yifu and Tian Guoqiang had a debate on it. They maintain that the positive role of local governments in China's economic development cannot be denied, but the negative effect of government "cross-border" behavior on economic development cannot be ignored, either (Wang and Ju 2012). In this context, an in-depth study on how PSA affects carbon emissions and how government intervention affects the relationship between them opens up a new path for the low-carbon economic development and environmental sustainability, and also fills in the theoretical gaps on these issues. Pitifully, few studies researched this field.

Accordingly, the possible contributions include the following aspects: ① This paper sorts out and analyzes the transmission mechanism of PSA on CO_2 emissions and systematically tests the impact of PSA on CO_2 emissions. ② The spatial Durbin model is used for econometric analysis to effectively reflect the typical characteristics of spatial correlation between CO_2 emissions and PSA. ③ The urban panel data is selected as the research sample to effectively reduce the error of estimation results caused by large spatial scale and internal differences. In addition, as for CO_2 emission data calculation, not only energy-related CO_2 emissions but also the impact of vegetation carbon sequestration is taken into account, making the data more accurately reflect the actual situation. ④ From the perspective of government intervention, the dynamic threshold model is used to explore the nonlinear characteristics of how government intervention impacts on CO_2 reduction effect of PSA, which enriches and develops the research on the influencing factors and mechanism of CO_2 emissions.

The rest of the sections are arranged as follows: The relevant literature is reviewed in "Literature review." The theoretical analysis and hypotheses are made in "Theoretical analysis and research hypothesis." The data source and model setting are shown in "Model setting and variable selection." "Empirical results analysis and discussion" illustrates the empirical results and makes discussions. The conclusions and policy implications are followed in "Conclusions and policy implications." The whole structure of the research is described in Fig. 1.

Literature review

The identification of factors affecting CO_2 emissions has always been a research hotspot in academic circles. Up to now, the key influencing factors mainly include economic growth (Govindaraju and Tang 2013; Kasman and Duman 2015; Dong et al. 2018), industrial structure (Tian et al. 2019; Pan et al. 2021), technological innovation (Yu and Du 2019; Wang and Zhu 2020; Chen and Lee 2020; Ikram et al. 2021), financial development (Shahbaz et al. 2013; Zhao and Yang, 2020), urbanization (Martínez-Zarzoso and

[1] Data are calculated according to *China Urban Statistical Yearbook*.

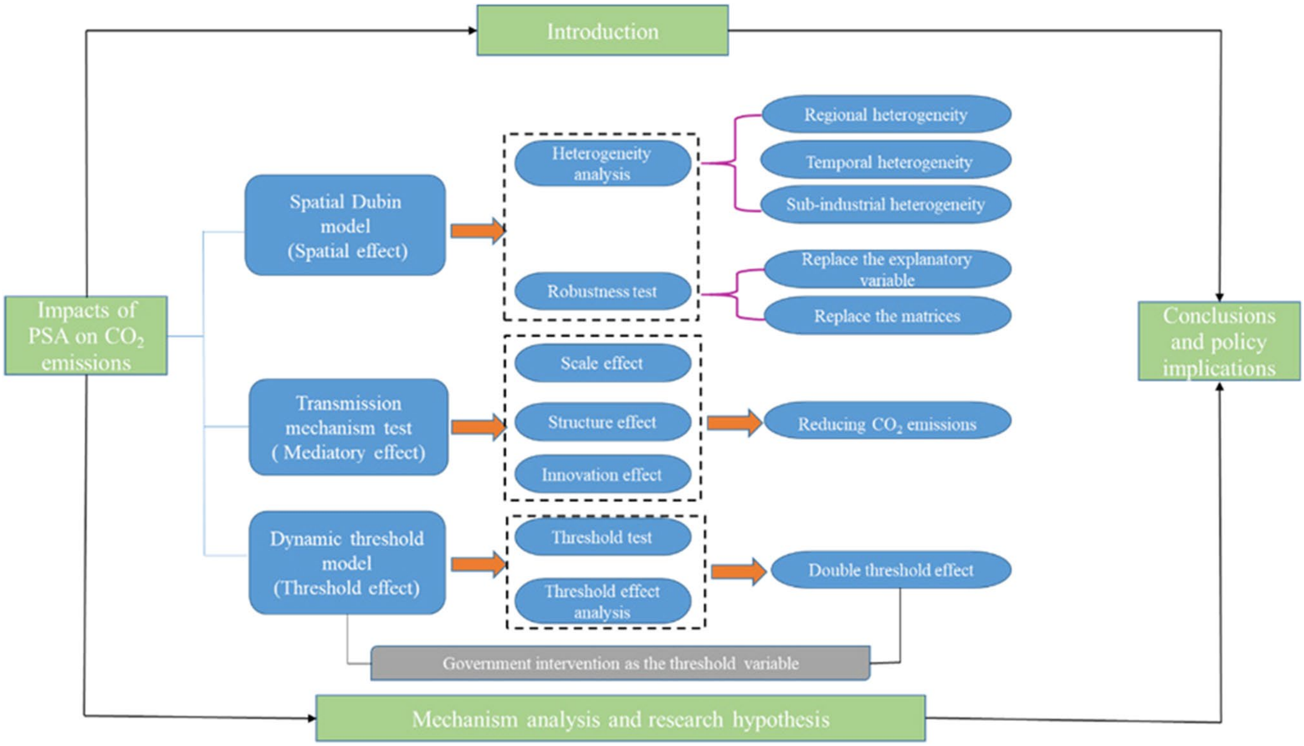

Fig. 1 Research structure

Maruotti 2011; Wang et al. 2018a), foreign trade (Hao and Liu 2015; Huang et al. 2019; Bakhsh et al. 2021), and industrial agglomeration (Chen et al. 2018; Wu et al. 2021a; Shen & Peng 2021). Among these factors, industrial agglomeration is most relevant to this paper, so the literature review of this paper is focusing on the relationship between industrial agglomeration and environmental pollution. Scholars are divided over the relationship between them. Three views are mainly included: first, some scholars hold that industrial agglomeration aggravates pollution emissions through expanding production scale (Wen and Liao 2019) and increasing energy consumption demand (Shen & Peng 2021). The second view is that the positive externalities brought by industrial agglomeration will promote environmental protection technology, so as to effectively control pollution emissions (Yang and Wang 2022). Guo et al. (2020) believe that industrial agglomeration can improve the environment, but there are regional heterogeneities. Industrial agglomeration enhances the environmental quality better in the east than in the central and western regions. The third view is that impacts of industrial agglomeration on environmental pollution show nonlinear characteristics. Ren-fa YANG (2015) argues that industrial agglomeration exerts an obvious threshold effect on environmental pollution, that is, if the industrial agglomeration level is below the threshold value, pollution will be intensified, and if it is higher than the value, pollution will be reduced.

At present, few pieces of literature are studying the impact of PSA on CO_2 emissions. The literature on the emission reduction effect of industrial agglomeration is mostly discussed from the perspective of manufacturing agglomeration. Most scholars believe that manufacturing agglomeration has a dual effect on pollution emission, which may aggravate pollution emission through expanding production scale (Lan et al. 2021) and increasing energy consumption demand (Cheng 2016) or reduce pollution emissions through technology spillover (Ikram et al. 2020; Abid et al. 2022), the specialized division of labor and economies of scale (Fang et al. 2020). Wang et al. (2018b) and Yuan et al. (2020) confirm that a significant inverted U-shaped relationship exists between manufacturing agglomeration and environmental pollution. The producer service industry is characterized by knowledge and technology-intensive, low-polluting, and low-emitting (Shao et al. 2017). Relying on its agglomeration effect, PSA brings knowledge and technology spillover, so as to alter the rough-oriented pattern of economic growth and reduce CO_2 emissions. Therefore, PSA has become a major contributor to realizing green and low-carbon circular economy. With the development of the producer service industry and the enhancement of the pulling effect of the service industry on the national economy, research on the CO_2 emission reduction effect of PSA is drawing many scholars' concern at home and abroad in recent years. Some scholars put PSA and CO_2 emissions in the same framework for theoretical and empirical research. Zhao et al. (2021b) utilized the balanced panel data of China's 30 provinces from 2003 to 2017 to test impacts of PSA on CO_2 emissions, finding that PSA can effectively mitigate the CO_2 emissions, but there is significant regional heterogeneity; Li et al. (2019) explore the impact of PSA on carbon intensity, concluding that the degree of misallocated resources greatly affects CO_2 emission reduction effect of PSA, and there exists a significant double-threshold effect.

To sum up, academic circles have systematically studied the impact of industrial agglomeration on environmental pollution, which provides a good research idea for this study. At present, the systematic research on industrial agglomeration and CO_2 emission reduction mostly focuses on the manufacturing industry. The research on the relationship between PSA and CO_2 emissions is still at the primary stage, and there is a lack of in-depth exploration on the internal mechanism, heterogeneity, and nonlinear characteristics. Accordingly, using the panel data of 268 Chinese cities over the period from 2005 to 2017, this paper systematically discusses the spatial impact of PSA on CO_2 emissions, its internal mechanism and non-linear characteristics by constructing spatial Durbin model, mediatory effect model, and dynamic threshold model so as to offer instructive guideline for early achieving carbon peak and carbon neutrality.

Theoretical analysis and research hypothesis

Analysis of the direct impact of PSA on CO_2 emissions

PSA can adjust market scale and openness, industrial structure, and stimulate economic growth by transferring and gathering factors such as population, capital, and resources, so as to improve energy efficiency and reduce CO_2 emissions (Binbin 2018; Yang et al. 2020). Compared with industry, producer services have a stronger agglomeration effect and technology-intensive characteristics; PSA can reduce pollution by deepening labor division, extending the industrial value chain and promoting production technology innovation (Francois 1990). Under the circumstances of prominent industrial structural contradictions and increasing pressure to conserve energy and reduce emissions, accelerating PSA has become a breakthrough to optimize the industrial structure and reduce CO_2 emissions, so as to effectively address the dilemma of "stabilizing growth and promoting emission reduction" (Chen et al. 2020a). According to MAR externality theory (Marshall and Guillebaud 1961), the agglomeration development of producer services can provide targeted professional services; effectively strengthen the sharing and diffusion of knowledge, information, and technology among enterprises; and improve the utilization efficiency of energy factors of enterprises; PSA can further promote industrial enterprises to use information technology, R&D, and design as intermediate inputs for production, and hence ultimately realize energy conservation and emission reduction in the process of industrial production. According to Jacobs' externality theory (Jacobs 2016), the diversified agglomeration of producer services increases the diversity and availability of outsourcing services for pollution emission reduction of industrial enterprises. At the same time, PSA helps to apply new environmental protection technologies and processes to the science and technology industry, improve the energy efficiency of enterprises, and achieve pollution emission reduction. Porter's externality theory holds that externality mainly comes from the competitive and professional division of labor in an open environment (Ambec et al. 2013). An open and shared environment is conducive to the formation of a healthy and benign competition mechanism and effectively curbs the spread of opportunism, and thus promotes the fine division of labor of industrial enterprises and a great demand for productive services (Wang et al. 2018b). In this manner, the quality of economic development is improved, and pollution emissions are effectively reduced. In addition, as a typical knowledge and technology-intensive industry, the producer services industry gathers a large number of excellent talents, producing a "learning effect" (Zhao et al. 2021b). Advanced production technology and innovation information produce a spatial spillover effect with the cross-regional flow of personnel (Chen and Lee 2020). Producer services and the manufacturing industry form a collaborative agglomeration model through the correlation between upstream and downstream industries. This collaborative agglomeration has a significant spatial spillover effect and spatial feedback mechanism. The spatial property of urban geographical location determines that the PSA will inevitably produce a spatial spillover effect, thus affecting the surrounding cities (Shao et al. 2017). Information consulting, finance, scientific research, and other high-end producer services are mostly located in regional central cities with the characteristics of low transaction frequency and wide service range, which has an obvious spillover impact on pollution emissions in surrounding areas.

Therefore, hypothesis 1 is proposed: PSA can inhibit CO_2 emissions and has a spatial spillover effect.

Analysis on the impact mechanism of PSA on CO_2 emissions

According to Grossman and Krueger (1995), Brock and Taylor (2005), the main ways to affect environmental pollution include scale effect, structure effect, and innovation effect. Therefore, this paper intends to analyze the mechanism of PSA affecting CO_2 emissions from the aspects of reducing energy consumption (scale effect), optimizing industrial structure (structure effect), and improving technological innovation (innovation effect).

1. Scale effect: The spatial agglomeration of producer services can enable infrastructure sharing and intensive utilization of production equipment, which helps manufacturers save production and transaction costs, while the embedding of an effective value chain can reduce resource consumption and CO_2 emissions through economies of scale. Specifically, upstream and downstream affiliated enterprises in the same industrial chain gather in the same region, which is conducive to sharing convenient transportation facilities to reduce logistics costs and energy consumption in the transportation process and achieving emission reduction effect. The industrial agglomeration of similar enterprises is easier to form a fully competitive market so as to reduce information asymmetry. Enterprises are forced to reduce prices and save costs, by controlling energy consumption, thus achieving emission reduction effect. Additionally, the centralized discharge and treatment of similar or homogeneous polluting wastes can reduce the environmental treatment cost of enterprises, improve the recycling efficiency of wastes, and minimize the damage to the environment caused by the production.
2. Structure effect: Producer services are an important part of the tertiary industry, and the agglomeration drives the development of the tertiary industry, promotes the optimization and upgrading of industrial structure, and reduces the demand for energy factors and pollutants emissions by improving the efficiency of resource allocation. What is more, PSA and its effective embedding in the manufacturing industry will also help to upgrade the structure of the manufacturing industry and improve production efficiency, achieving pollution reduction. In short, as a modern service industry with low pollution and high added value, PSA can rationally optimize the allocation of resources, effectively improve the industrial structure, and gradually reduce the proportion of the industry, thus reducing CO_2 emissions.
3. Innovation effect: Technology spillover can stimulate the innovation potential of enterprises. Enterprises can reduce CO_2 emissions by using advanced technology and energy-saving equipment to change the energy consumption structure (Ikram et al. 2022). Specifically, producer services effectively embed advanced production technology, professional theoretical information, and cutting-edge innovative ideas into production and manufacturing links in the form of intermediate investment; promote a large number of scientific and technological R&D and technological competition, so as to improve the product design and scientific management ability, energy utilization efficiency, and pollution control level of the manufacturing industry; and finally achieve the effect of energy conservation and emission reduction. Besides, manufacturing enterprises use advanced energy-saving equipment and clean energy to replace backward and aging production equipment and fossil energy. These are conducive to reducing CO_2 emissions.

Based on this, hypothesis 2 is put forward: PSA indirectly inhibits CO_2 emissions through reducing energy consumption, optimizing the industrial structure and improving technological innovation.

Analysis on the threshold effect of government intervention

In China's political system, the promotion of local officials presents a vertical form from top to bottom, so the political promotion of local officials is a direct driving force for the government to intervene in economic development (Wu, et al. 2020a). At the initial stage of the development of producer services, marketization has not been completed, and the decisive role of the market in resource allocation is not prominent. Government intervention has become necessary and important, and its functions encompass four aspects:

First of all, government intervention has improved the market failure caused by externality and information asymmetry at the initial stage of the producer services development (Zhao et al. 2021a). The government conducts rectification through intervention, which reduces market friction and improves the efficiency of resource allocation (Wang et al. 2021). Second, government intervention provides an endogenous impetus for the development of producer services, which is specifically reflected in the government's promotion and improvement of economic development and quality by optimizing the expenditure structure and increasing investment in science, technology, and education (Xie et al. 2019). Third, government intervention promotes the rational flow of talents and resources in agglomeration areas of producer services, which will trigger benign competition among governments and help to address problems such as unbalanced development among regions (Sun and Huang, 2020). However, under the institutional background of fiscal decentralization, the original "GDP-only theory" will lead to serious distortion of resource allocation and imbalance of industrial structure (Li et al. 2022). Specifically, excessive government intervention will lead to a false agglomeration trend in industrial agglomeration areas (Wei and Wu 2021). The cause is that enterprises enter the agglomeration areas to pursue "policy rent" and maximize their interests. The entry of more inefficient enterprises accelerates false agglomeration, resulting in resource waste and mismatch (Hao et al. 2020). For different types of enterprises, the impact of government intervention on resource mismatch also shows heterogeneity (Zhang et al. 2021). For example, in the state-owned economic sector, government intervention can balance the financing cost of enterprises, so as to alleviate the financial resource mismatch, while in the private economic sector, it is just the opposite. Therefore, the different degrees of government intervention will make PSA have a different impact on resource allocation, thus differently affecting CO_2 emissions.

Accordingly, hypothesis 3 is assumed: Government intervention may have a threshold effect, namely, the appropriate intervention will make PSA inhibit CO_2 emissions, whereas excessive intervention will aggravate CO_2 emissions.

Model setting and variable selection

Model setting

Spatial measurement model setting

STIRPAT model[2] is one of the important theoretical frameworks to study the influencing factors of environmental pollution (Wu et al. 2021b). Based on the research paradigm of Elhorst J P, this paper utilizes the general form of STIRPAT model to deeply analyze and discuss the influencing mechanism of PSA on CO_2 emissions. Since STIRPAT model can decompose and improve the influencing factors, this paper will further expand it according to EKC hypothesis. In addition, the spatial dependence among variables is not only reflected in the interaction between regions in the current period but also the time inertia due to the endogenous factors of variables (Chen et al 2019). Accordingly, referring to Wang and Zheng (2021), this paper introduces the dynamic spatial Durbin model into the STIRPAT model to verify the spatial spillover effect of PSA on CO_2 emissions. The model is constructed as follows:

$$\begin{aligned}1\text{n } CO_{2i,t} &= \beta_1 1\text{n } CO_{2i,t-1} + \rho_1 W 1\text{n } CO_{2i,t} \\ &+ \beta_2 1\text{n } PJ + \rho_2 W 1\text{n } PJ + \beta_3 X_{i,t} \\ &+ \mu_i + \lambda_t + \varepsilon_{i,t}\end{aligned} \tag{1}$$

where i is the city; t is time; CO_2 represents carbon emissions; PJ indicates the agglomeration level of producer services; X consists of control variables; β_1 represents the regression coefficient of the first lag period, which is the impact of CO_2 emissions of the previous period on the current period; ρ_1 is the spatial lag coefficient, which reflects the impact of surrounding regional CO_2 emissions; ρ_2 represents the spatial lag coefficient of PSA, which reflects the impact of PSA on CO_2 emissions in adjacent areas. W represents the spatial weight matrix. In this paper, the reciprocal square weight matrix of distance that can comprehensively reflect the spatial correlation between cities is adopted. The specific element setting method is as follows:

$$w_{ij} = \begin{cases} 1/d_{ij}^2, i \neq j \\ 0, i = j \end{cases} \tag{2}$$

Diagonal elements of the spatial weight matrix are 0, and d_{ij} is the geographical distance between the two cities.

Dynamic threshold model setting

According to the theoretical research, it is assumed that the impact of PSA on CO_2 emissions will show nonlinear characteristics due to different degrees of government intervention. In order to verify this nonlinearity and alleviate the potential endogeneity of the traditional regression model, referring to Wu et al. (2019), this paper constructs the dynamic threshold effect model:

$$1\text{n } CO_{2i,t} = \begin{array}{c}\mu_i + 1\text{n}CO_{2i,t-1} + \beta 1\text{n } PJ_{i,t} + \delta X_{it} + \lambda_1 1\text{n } PJ_{i,t} \times I(1\text{n } GOV_{i,t} \le \gamma_1) \\ +\gamma_2 1\text{n } PJ_{i,t} \times I(\gamma_1 < 1\text{n } GOV_{i,t} \le \gamma_2) + \lambda_3 1\text{n } PJ_{i,t} \times I(1\text{n}GOV_{i,t} > \gamma_2) + \varepsilon_{i,t}\end{array} \tag{3}$$

where λ_1, λ_2 and λ_3 respectively represent the impact coefficient of PSA on CO_2 emissions under the different threshold range of government intervention; $1\text{n}GOV$ represents a threshold variable, γ is the threshold estimated value, γ_1 and γ_2[3] represents the first threshold value and the second threshold value respectively, I represents the indicator function, and the definitions of other variables are the same as in model (1).

Variable setting and data source

Explained variable

Carbon emissions (CO_2) The available literature on CO_2 emission solely focuses on carbon emissions related to energy, while the impact of vegetation carbon sequestration has been ignored. Shan et al. (2016) use the CO_2 emission coefficient provided by IPCC and 11 energy such as coal,

[2] Ehrlich and Holdren (1971) first proposed IPAT model as a framework to study the impact of population growth on the environment. However, the IPAT equation does not take into account the differences in the sensitivity of the dependent variables to the influencing factors and cannot observe the impact of factors other than population, affluence, and technology on environmental pressure. In order to overcome the limitation of this model, Dietz and Rosa (1994) established the stochastic form of IPAT–STIRPAT model.

[3] In order to explain the structure of the model easily, it is assumed that there are two effective thresholds, which should be determined according to the estimation results of the model.

coke, gas, and natural gas to calculate CO_2 emissions. In reality, vegetation has a significant impact on CO_2 adsorption, accounting for the main part of CO_2 emissions from energy consumption (Cox et al. 2000). Ignoring this part of carbon emissions will lead to inaccurate data of CO_2 emissions.[4] This paper uses the carbon emission data measured by Chen et al.'s (2020b). The data is currently the most comprehensive urban carbon emissions dataset for cities that have been peer-reviewed and cross-validated in multiple rounds.

Explanatory variable

The level of PSA (PJ) Referring to Yuan et al. (2020), this paper uses the location entropy model which can eliminate the endogenous impact caused by regional-scale differences to measure the level of PSA. The greater the location entropy, the more mature the development of the industry in this region, the stronger the agglomeration capacity, and the more scale advantages and comparative advantages compared with other regions in China. The calculation method is as follows:

$$PJ_{i,j} = {}^{e_{i,j}/E_j}\Big/_{e_i/E} \tag{4}$$

where $e_{i,j}$ refers to the number of employees in i city j industries; E_j indicates the total number of employees in the national j industry; e_i indicates the total number of employees in all industries in the city i; E indicates the total number of employees in all industries in the country. Based on the research of Ke et al. (2014), the sub-industries of the service industry with intermediate demand rate greater than 60% are defined as producer services, including "transportation, warehousing, post and telecommunications(TWPT)," "leasing and commercial services(LCS)," "wholesale and retail trade," "finance(WRT)," "information transmission, computer services and software(ITCSS)" "Scientific research, technical services and geological exploration(SRTSGE)."

Threshold variable

Government intervention (GOV) Referring to Ma et al. (2021), this paper uses the ratio of local fiscal expenditure to GDP to measure the level of government intervention. The greater the ratio, the lower the marketization level and the more government intervention.

[4] This method uses the particle swarm optimization backpropagation (PSO-BP) algorithm to unify the scale of DMSP/OLS and NPP/viirs images from 1997 to 2017 and then utilize the PSO-BP algorithm to reduce the size of energy carbon emission based on Provincial night lighting data.

Control variables

1. Population density (POP): It can mirror the relationship between population and space in a region. The larger the population density, the more environmental and social problems it will bring, which will also affect CO_2 emissions (Martínez-Zarzoso and Maruotti 2011). POP is measured by the ratio of resident population at the end of the year to the total area of urban jurisdictions.
2. Foreign direct investment (FDI): FDI can improve production efficiency and reduce energy consumption through technology correlation and knowledge spillover. On the other hand, it may also transfer high-pollution industries, resulting in pollution transfer (Hao and Liu, 2015). It is reflected by the proportion of the annual actual amount of foreign investment in GDP.
3. Human capital (HUM): The improvement of human capital is conducive to the development of local energy conservation and emission reduction technologies (Chen and Lee 2020). The number of people with bachelor's degrees or above among the employed population in each city is used as the proxy variable of human capital level.
4. Financial development (FIN): A higher financial development level can transfer funds from inefficient departments to efficient departments, so as to enhance the efficiency of the overall economic system (Li, et al. 2019). It is expressed by the proportion of the year-end deposit and loan balance of financial institutions in GDP.

Data sources and descriptive statistics of variables

Given the availability of data, this paper samples 268 Chinese cities from 2005 to 2017. The original data of CO_2 emissions come from county carbon emission data published by CEADs. The original data of other variables come from the China Urban Statistical Yearbook, China Environmental Yearbook, the official website of the National Bureau of Statistics, the official website of provincial and municipal statistical bureaus, and the EPS database. Some missing data are supplemented by interpolation. The descriptive statistics of variables are shown in Table 1.

Empirical results analysis and discussion

Based on the externality of PSA, a spatial econometric model is employed to investigate the impact of PSA on CO_2 emissions and the spatial spillover effect.

Table 1 Variable description statistics

Variable	Obs	Mean	Std. Dev	Min	Max
lnCO_2	3484	2.9813	0.7729	0.5443	5.6283
lnPJ	3484	−0.1654	0.3124	−2.0103	1.1535
lnPOP	3484	5.7457	0.9035	1.5475	7.8866
lnFDI	3484	2.635	1.4353	−5.8385	6.8062
lnHUM	3484	−0.1641	1.3901	−36.84	2.6503
lnFIN	3484	1.3029	0.6069	−4.2008	4.0508
lnRGDP	3484	10.3021	0.7466	8.0591	15.6752
lnIND	3484	−0.1814	0.3426	−1.8532	1.0778
lnINNOV	3484	6.4182	1.8617	0	11.8428

Analysis of spatial effect results

Spatial autocorrelation analysis

The spatial correlation of variables should be tested first. Moran's I is used to examine the spatial correlation of carbon emissions. The results in Table 2 reveal that the Moran index of CO_2 emissions fluctuated between 0.043 and 0.0447 from 2005 to 2017, indicating that Chia's CO_2 emissions show a significant spatial positive correlation, further verifying that it is appropriate to use the spatial measurement model for empirical test. In order to further present the spatial agglomeration characteristics of CO_2 emission levels, the local Moran scatter diagrams in 2005 and 2017 are presented in Fig. 2. It can be seen that the scatter points are mainly distributed in the first quadrant (high-high agglomeration) and the third quadrant (low-low agglomeration), and as time goes on, the concentration trend of CO_2 emissions mainly moves to the first quadrant (high-high agglomeration) and the second quadrant (low–high agglomeration). Overall, there is a significant spatial correlation between CO_2 emission levels in local cities.

Selection and test of spatial metrology model

Considering the spatial correlation of CO_2 emissions, this paper preliminarily sets the model as the bidirectional fixed spatial Durbin model (SDM) and carries out a correlation test. According to the test results in Table 3, the bidirectional fixed spatial Durbin model (SDM) is appropriate.

Analysis of benchmark regression

In order to eliminate the endogeneity in spatial regression, the estimation result of the system generalized estimation method (SYS-GMM) is introduced (Wu et al 2020b). In addition, the estimation results of SAR and SEM are also listed for checking the robustness. The estimations in Table 4 show that the magnitude, direction, and significance of the estimated coefficients of the core variables in all models are consistent, indicating that the estimations are scientific and robust. The following main analyzes the spatiotemporal fixed effect results of the dynamic spatial Durbin model. From the perspective of the time dimension, the regression coefficient of CO_2 emissions in the first lag phase (CO_{2t-1}) is positive at the 1% significance

Table 2 Moran index of CO_2 emissions from 2005 to 2017

Year	2005	2006	2007	2008	2009	2010	2011
Moran's I	0.047***	0.045***	0.047***	0.049***	0.046***	0.046***	0.047***
Z-Value	7.371	7.071	7.276	7.524	7.19	7.137	7.171
Year	2012	2013	2014	2015	2016	2017	
Moran's I	0.047***	0.045***	0.044***	0.047***	0.046***	0.043***	
Z-Value	7.17	6.802	6.734	7.061	6.997	6.604	

***Significance at 1% level

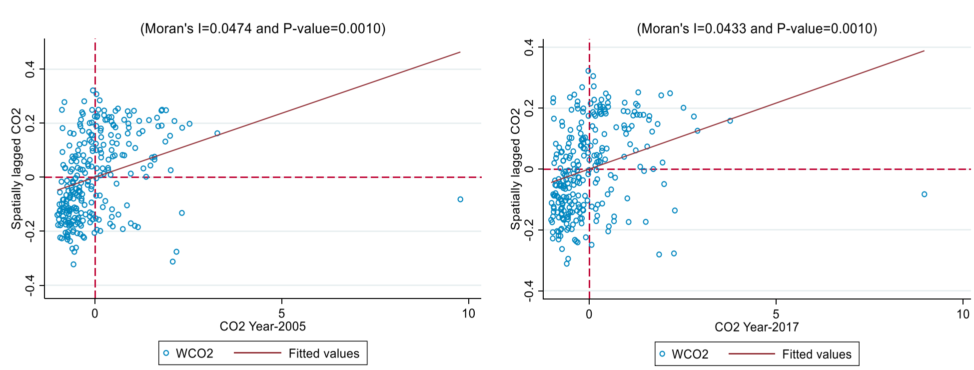

Fig. 2 Scatter diagram of Moran's I index of CO_2 emissions in China

Table 3 Test results of spatial econometric model selection

Index	Value	*p*-value	Index	Value	*p*-value
LM-lag	620.069***	0.000	LM-error	706.894***	0.000
Robust LM-lag	4.105**	0.043	Robust LM-error	90.929***	0.000
LR-lag	22.53***	0.002	LR-error	23.74***	0.001
WALD-SAR	22.55***	0.002	WALD-SEM	23.69***	0.001
Hausman	5.32***	0.005			

**Significance at 5% level; ***significance at 1% level

Table 4 Benchmark regression estimation results

Variable	(1) SYS-GMM	(2) SAR	(3) SEM	(4) SDM
L.lnCO_2	0.8032*** (63.74)	0.7736*** (34.69)		0.7779*** (35.77)
lnPJ	−0.264*** (−20.74)	−0.8146*** (−3.28)	−0.8321*** (−3.17)	−0.6716** (−2.44)
lnPOP	0.1467***(54.77)	0.0867** (0.82)	0.0889* (0.75)	0.0204** (0.15)
lnFDI	−0.0148*** (−3.35)	−0.2132** (−2.34)	−0.2598*** (−2.74)	−0.3349** (−3.46)
lnHUM	−0.0659*** (−3.56)	−0.1197** (−1.96)	−0.1047** (−1.63)	−0.0582* (−0.87)
lnFIN	−0.4593*** (−13.18)	0.1388* (1.11)	0.169 (1.32)	−1.6576** (−1.65)
W*lnPJ				−0.4538**(0.26)
AR (1)	−3.94 [0.000]			
AR (2)	0.64 [0.520]			
Hansen	267.27[0.99]			
ρ or λ		0.8583***(23.41)	0.8591***(25.53)	0.8377***(20.21)
R^2		0.324	0.205	0.587

Z-values are in () and P-values are in []

*Significance at 10% level, **significance at 5% level and ***significance at 1% level

level. The direct effect and spatial spillover of PSA on CO_2 emissions are significantly negative, indicating that PSA has an obvious inhibitory effect on CO_2 emissions in the local and its adjacent areas. In terms of control variables, population density is positively significant. The reason is that too many people will consume more energy, leading to an increase in CO_2 emissions. The coefficient of FDI is significantly negative, implying that FDI, as a strategic means of the market for technology in China, significantly improves the production efficiency of the manufacturing industry through the technology spillover effect (Dong et al. 2019), which is conducive to CO_2 emission reduction. The coefficient of human capital is significantly negative, mainly because the improvement of human capital level can make the spillover effect of technology and knowledge give full play, bring advanced technology and management experiences to enterprises, improve production efficiency, and reduce CO_2 emissions (Abel and Deitz 2011). The coefficient of financial development level (FIN) is significantly negative, indicating that the development of the financial industry can optimize the allocation of financial resources, provide financial support for technological innovation of industries and enterprises, and help to promote the progress of environmental protection technology (Wang and Tan 2021), so as to reduce CO_2 emissions.

Heterogeneity analysis

Considering the differences in regions, time nodes, and subindustries, this paper further explores the differential impact of PSA on CO_2 emissions.

① Regional heterogeneity: 268 cities are divided into two sample groups for regression: the east (95) and the central and western (173). Columns (1) and (2) in Table 5 show that impacts of PSA on CO_2 emissions vary in the eastern and central and western regions. PSA significantly inhibited CO_2 emissions in the eastern region whereas significantly promoted the central and western regions. ② Temporal heterogeneity: The State Council issued *the Guiding Opinions on Accelerating the Development of Producer Services and Promoting the Adjustment and Upgrading of Industrial Structure* in 2014 (hereinafter referred to as *Opinion*). In order to further explore whether the impacts of PSA on CO_2 emissions are divergent before and after the implementation of the policy, based on the issuing time of the *Opinion*,

Table 5 Estimation results of regional and temporal heterogeneity

Variable	Regional heterogeneity		Temporal heterogeneity	
	(1)	**(2)**	**(3)**	**(4)**
	Eastern region	Central and western region	2005–2013	2014–2017
lnPJ	−2.5549** (−2.24)	1.4837*** (3.07)	0.4802 (0.73)	−0.9053*** (−2.87)
W*lnPJ	3.6742 (0.59)	11.073** (2.53)	−13.195* (−1.65)	−9.63*** (−2.87)
Control	Yes	Yes	Yes	Yes
Time-fixed	Yes	Yes	Yes	Yes
City-fixed	Yes	Yes	Yes	Yes
ρ	0.4974***	0.8260**	0.8480***	0.8340***
	(5.82)	(18.5)	(18.08)	(10.96)
R^2	0.632	0.439	0.281	0.326

Z-values are in ()

*Significance at 10% level; ** significance at 5% level; *** significance at 1% levels

Table 6 Estimation results of industry heterogeneity

Variable	Sub-industry					
	WRT	TWPT	ITCSS	FIN	LCS	SRTSGE
lnPJ	0.4215*** (3.14)	0.0046*** (0.03)	−0.7793*** (−2.71)	−0.4201***(−3.14)	0.6706*** (2.97)	−0.2504*** (−0.8)
W*lnPJ	−0.5879 (−0.56)	5.2577*** (3.41)	−1.748* (−0.6)	−0.9902 (−0.79)	0.1056 (0.05)	−6.9024* (−1.92)
Control	Yes	Yes	Yes	Yes	Yes	Yes
Time-fixed	Yes	Yes	Yes	Yes	Yes	Yes
City-fixed	Yes	Yes	Yes	Yes	Yes	Yes
ρ	0.838*** (20.24)	0.8269*** (18.84)	0.8373*** (20.16)	0.838*** (20.24)	0.8382*** (20.27)	0.8374*** (20.16)
R^2	0.37	0.511	0.25	0.36	0.46	0.38

Z-values are in ()

*Significance at 10% level; ***significance at 1% levels

the samples are divided into two stages: 2005–2013 and 2014–2018. The results in columns (3) and (4) in Table 5 show that the impact of PSA on CO_2 emissions has changed from being insignificant in the previous stage to significantly inhibit. ③ Industry heterogeneity: Table 6 reveals that the agglomeration of sub-industries of producer services has different impacts on CO_2 emissions. TWPT, LCS, and WRT are at the low end of the value chain, and their agglomeration intensifies the CO_2 emissions of local and surrounding cities; ITCSS, FIN, and SRTSGE have the advantages of technology driving and knowledge relevance. Their agglomeration and development will not only reduce local CO_2 emissions but also contribute to the CO_2 emission reduction of surrounding areas.

Robustness test

1. Replace the explanatory variable

Referring to the research of Liu et al. (2020), this paper uses employment density (ED) as an alternative index to reflect the agglomeration degree of producer services. ED measures the spatial agglomeration degree of an industry by calculating the number of employees per unit area of industry. The greater the density, the higher the regional concentration of the industry. The calculation formula is as follows:

$$ED_{i,t} = {}^{x_{i,t}}\Big/_{area_i} \tag{5}$$

where i and t represent the city and year respectively, ED refers to the employment density of an industry, x refers to the number of employees in an industry, $area$ refers to the land area of the administrative region of the city.

2. Replace the matrices

In the econometric model, the weight matrix is exogenous. This paper uses the adjacency weight matrix and economic distance weight matrix to regress the spatial Durbin model again to confirm the robustness of the results.

Table 7 Estimation results of the robustness test

Variable	ED as the explanatory variable		W^c and W^e as matrices	
	(1)	(2)	(3)	(4)
	SYS-GMM	SDM	W^c	W^e
L.GTFP	0.8054*** (4.221)	0.7756*** (3.521)	0.8788*** (3.756)	0.8123*** (3.625)
lnPJ	− 0.2546*** (− 40.74)	− 0.7885** (− 2.75)	− 0.8254*** (− 3.14)	− 0.9182***(− 3.58)
W*lnPJ		− 1.7818** (− 0.61)	− 6.5222** (− 1.38)	− 1.3646**(− 1.98)
Control	Yes	Yes	Yes	Yes
Time-fixed	Yes	Yes	Yes	Yes
City-Fixed	Yes	Yes	Yes	Yes
AR(1)/AR(2)	[0.000]/[0.5312]			
Hansen	[0.999]			
ρ		0.8403** (24.15)	0.1745*** (43.29)	0.158*** (43.73)
R^2		0.4235	0.262	0.39

Z-values are in () and P-values are in []

**Significance at 5% level and ***Significance at 1% level

1. Adjacency weight matrix (W^c). If two cities are geographically adjacent, $W^c_{ij} = 1, (i = j)$; otherwise, $W^c_{ij} = 1, (i = j)$
2. Economic distance weight matrix (W^e). The weight setting adopts the reciprocal of the absolute value of the economic development level gap between the two cities $W^e_{ij} = 1/\left|\overline{e}_i - \overline{e}_j\right|, (i \neq j), W^e_{ij} = 0, (i = j)$ where $\overline{e}_i$ represents the regional average GDP corrected by the GDP deflator.

It can be seen in Table 7 that either replacing the explanatory variable or the matrices, the symbols, coefficients, and significance of the core variables are consistent with the previous estimations in Table 4, which further proves that the setting of the model and the regression results are reliable and robust.

Transmission mechanism test

According to the above regression results, PSA has an inhibitory effect on urban CO_2 emissions. So how does PSA curb CO_2 emissions? This paper will identify and test the mechanism from three channels: scale effect, structure effect, and technology effect. Among them, scale effect is measured by per capita GDP. Structure effect is measured by the proportion of tertiary industry in the secondary industry. Technical effect is expressed in the number of patent applications authorized. Referring to Baron and Kenny (1986), three regression equations are constructed for mediating effect test.

$$1nCO_{2it} = \alpha_0 + \alpha_1 1nPJ + \alpha_2 X_{it} + \mu_{it} \tag{6}$$

$$M_{it} = \beta_0 + \beta_1 1nPJ + \beta_2 X_{it} + \mu_{it} \tag{7}$$

$$1nCO_{2it} = \theta_0 + \theta_1 1nPJ + \theta_2 \mu_{it} + \theta_3 X_{it} + \mu_{it} \tag{8}$$

where X represents a set of control variables; M are possible intermediary variables, including per capita (RGDP), industrial structure (IND), and technological innovation (INNOV).

Columns (1)–(3) in Table 8 show the impacts of PSA on CO_2 emissions when economies of scale are taken as the intermediary variable. Column (1) shows that the total effect of PSA on CO_2 emissions is − 5.765, which is significant at the level of 1%. Column (2) shows the regression of PSA to urban economies of scale. The coefficient of economies of scale is significantly positive at the level of 1%, indicating that PSA significantly promotes urban economies of scale. Column (3) shows that the CO_2 emission level is affected by economies of scale and PSA. All coefficients are significantly negative at the level of 1%, and the absolute value of the coefficient θ_1 (− 5.5026) of PSA is less than the absolute value of α_1 (− 5.765), indicating that PSA can indirectly inhibit the CO_2 emission level by promoting urban economies of scale; Sobel test and bootstrap test are significant at the level of 5%, which also verifies that the intermediary effect exists significantly, and the proportion of intermediary effect in the total effect is 16.54%. Similar analyses are made when industrial structure and technological innovation are intermediary variables. The results show that the intermediary effect of industrial structure accounts for 13.47% of the total effect, and that of technological innovation accounts for 44.52% of the total effect. The hypothesis H2 is verified.

Table 8 Test results of the transmission mechanism

Intermediary effect		Scale effect		Structure effect		Innovation effect	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Explained variable	$lnCO_2$	lnRGDP	$lnCO_2$	lnIND	$lnCO_2$	lnINNOV	$lnCO_2$
lnPJ	−5.765*** (−4.11)	−1.3833*** (−2.05)	−5.5026*** (−3.89)	−0.0387*** (−1.9)	−4.9882*** (−3.71)	−0.3365*** (−3.34)	−2.5963***(−2.13)
M			−1.3833** (−2.05)		2.062** (1.93)		6.1912*** (3.27)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	2.1548*** (0.73)	9.2146*** (12.454)	14.8741*** (2.16)	−12.778*** (−2.97)	14.2401*** (5.02)	4.4613*** (20.45)	−25.4664*** (−9.16)
Sobel		0.7816		−0.7667		−2.083	
		($Z=2.035$, $P=0.041$)		($Z=-1.894$, $P=0.058$)		($Z=-3.3154$, $P=0.001$)	
Indirect effect proportion		16.54%		13.47%		44.52%	
R^2	0.701	0.409	0.712	0.682	0.949	0.175	0.264

Z-values are in ()

**Significance at 5% level; ***Significance at 1% levels

Threshold effect analysis

According to the previous theoretical analysis, the impact of PSA on CO_2 emissions may have nonlinear characteristics due to different degrees of government intervention. Therefore, the dynamic threshold effect with government intervention as the threshold is analyzed.

Validity test of the threshold value

The first step is to estimate the dynamic threshold panel model for testing its effectiveness through threshold value. The estimation results are as follows:

As shown in Table 9, single and double thresholds are significant at the 1% level, but the triple threshold failed the test. The results indicate that government intervention has a double threshold effect. Table 10 presents the threshold estimations and confidence intervals of the double threshold model.

Estimation results of double threshold panel model

As shown in Table 11, PSA has a divergent impact on CO_2 emissions under different degrees of government intervention: when the level of government intervention is below the threshold value of 0.1719, the coefficient of PSA is −0.4934 and significant at 1% level, indicating that PSA can significantly inhibit CO_2 emissions. When the government intervention level is beyond the threshold value of 0.1719, the coefficient of PSA is 0.1898 and significant at 1% level, indicating that PSA significantly promotes CO_2 emissions, but the coefficient is smaller, and the promotion effect is weaker. When the level of government intervention reaches 0.8210, the impact of PSA on CO_2 emissions is significantly positive with a coefficient of 0.5816, which is as 3.06 times as that of the previous threshold, indicating that excessive government intervention will greatly aggravate CO_2 emissions.

Discussion on the empirical results

Discussion on the benchmark regression

The benchmark regression in Table 4 shows that China's CO_2 emissions have significant "time inertia," that is, if the CO_2 emissions in the current period are at a high level, the CO_2 emissions level in the next phase may go on increasing, showing the "snowball effect." The reason may be that

Table 9 Threshold estimation and test results

Model	F-statistics	P-value	BS number	Critical value		
				1%	5%	10%
Single threshold test	69.05	0.000	300	37.47	30.64	26.99
Double threshold test	32.78	0.003	300	27.60	23.89	21.11
Triple threshold test	16.64	0.5833	300	36.13	32.29	30.04

Table 10 Threshold estimations and confidence intervals

	Threshold estimations	95% confidence intervals
Threshold value γ_1	0.1719	[0.1621,0.1823]
Threshold value γ_2	0.8210	[0.8067,0.8267]

the adjustment of some economic policies, such as the optimization of industrial structure, population agglomeration, and technological progress has a time lag (Li et al. 2017), resulting in the lag of the change in CO_2 emissions. PSA has an obvious inhibitory effect on CO_2 emissions in the local and its adjacent areas. The reason is that PSA makes the internal division of labor tend to be more reasonable and the production more efficient, which improves the utilization efficiency of energy and promotes the manufacturing industry to accelerate the R&D of clean technologies and extend the industrial chain (Zhao et al. 2021a). In addition, it can also provide diversified and complementary technical services for the manufacturing industry of the city and adjacent cities and contribute to the technological innovation of the manufacturing industry, thus significantly inhibiting CO_2 emissions in the local and adjacent cities (Liu et al. 2018).

Discussion on the heterogeneous influence

Table 5 shows that impacts of PSA on CO_2 emissions vary in the eastern and central and western regions. Most cities in the eastern region have entered the period of urbanization, the industrial chain has extended to the high-end producer service industry with innovative elements such as technology, information, and knowledge, the spillover of technology and knowledge has been brought into play, and its agglomeration has significantly inhibited CO_2 emissions (Lan et al. 2021). In contrast, most cities in the central and western regions are in the middle and late stages of industrialization. Producer services are mainly at the middle and low end of the value chain with low technology content. In order to promote their development, a large amount of energy is invested, which will aggravate CO_2 emissions (Huang et al. 2019).

The results in columns (3) and (4) in Table 5 show that the impact of PSA on CO_2 emissions has changed from being insignificant in the previous stage to significantly inhibit. The reason is that the *Opinions* have made a clear positioning for producer services and provided a policy basis for the development of producer services, which clarifies the development orientation and leads them to develop green and environmental protection industries (Lin and Chen 2021). Therefore, after the promulgation of the Opinions, PSA is conducive to CO_2 emission reduction.

Table 6 shows that the agglomeration of sub-industries of producer services has different impacts on CO_2 emissions. "WRT," "TWPT," and "LCS" are at the low end of the value chain, and their agglomeration and development will bring about some problems such as urban congestion, repeated construction of roads, tracks, and other infrastructure, which will aggravate the CO_2 emissions of local and surrounding cities (Lin and Chen 2021). On the contrary, as for the high-end producer services at the top of the industrial chain such as "ITCSS," "FIN," and "SRTGE," which have the advantages of technology driving and knowledge relevance, their agglomeration and development can greatly promote technology diffusion and innovation along with productivity in the whole region (Iammarino et al. 2019). Therefore, it will not only reduce local CO_2 emissions but also have a learning and demonstrating effect on the surrounding areas, bringing about a positive technology spillover effect, which will contribute to the CO_2 emission reduction in the surrounding areas.

Discussion on the results of transmission mechanism

The transmission mechanism test shows that PSA can indirectly inhibit CO_2 emissions through economies of scale, industrial structure upgrading, and technological innovation. Comparing the three intermediary effects, the technological innovation effect is leading first, followed by economies of scale and industrial structure. This implies that PSA, especially PSA at the high-end value chain, stimulates the innovation potential of enterprises through technology spillover. Enterprises are more inclined to use advanced technology and energy-saving equipment to change the energy consumption structure, and thus reduce CO_2 emissions (Abid et al. 2021). Besides, the inhibition of scale effect and structure effect is limited. The reason is that currently, China's economy is experiencing rapid development; the secondary industry is still in an important position, and the proportion in the industrial structure may be relatively higher. Only the "green" upgrading of the industrial structure can effectively curb CO_2 emissions (Tian et al. 2019).

Table 11 Threshold effect estimation results

Explained variable	Elasticity coefficient	*T*-value	*P*-value
lnPJ	−0.26409***	−20.74	0.000
λ_1	−0.4934***	−5.02	0.000
λ_2	0.1898***	3.71	0.000
λ_3	0.5816***	9.48	0.000
Hansen test		267.27	1.000
AR(1)		−3.94	0.000
AR(2)		0.64	0.520

***significance at 1% level

Discussion on threshold effect

The threshold effect shows that PSA has an obvious double-threshold effect on China's CO_2 emissions under different levels of government intervention. The resource allocation effect of PSA is affected by government intervention. For example, in terms of talent introduction and investment attraction, the government can provide a series of subsidies and preferential policies, which will have a positive impact on the factor market and resource allocation. Therefore, in the process of industrial agglomeration affecting CO_2 emissions, the market usually plays a regulatory role, but when marketization has not been completed, the market fails to play the decisive role in resource allocation (Zhang et al. 2020b). Under the background of optimization and upgrading of industrial structure, China's economic development and transformation are currently at a crucial stage. The degree of marketization varies greatly in different regions. Imperfect marketization mechanism usually leads to problems such as weak consciousness of property rights protection, closed institutional environment, and even corruption. Therefore, when there is an excessive agglomeration of producer services, the government should timely guide by taking macro-intervention to adjust the industrial agglomeration to the process of coordinated development with resources and environment. As a result, the agglomeration effect may be affected by government intervention. Moderate government intervention can reduce energy consumption and achieve the effect of CO_2 emission reduction by optimizing resource allocation. At the same time, the government is the "night watchman" for industrial development and environmental quality improvement, which affects industrial agglomeration and diffusion. PSA reduces CO_2 emissions by promoting the flow of production factors to low-cost and resource-saving sectors, selecting the best location for development, realizing the optimal allocation of production factors, and changing resource consumption intensity and energy conversion. However, excessive government intervention will lead to distortion in factor markets and subsidies (Lin and Chen 2018). In addition, local governments stimulate the economy by using various policy means to promote industries that do not have comparative advantages, thus distorting factor prices and causing efficiency losses. In short, moderate government intervention is not only conducive to reducing the risk cost of technological innovation but also to alleviating market failure. Excessive government intervention may cause the misallocation of the resources and not be conducive to the operation of market economic mechanisms, leading to the increase of CO_2 emissions (Wang and Ju 2012).

Conclusions and policy implications

Based on the nightlight data to calculate the CO_2 emissions of 268 cities in China from 2005 to 2017, this study deeply explores the impact and transmission mechanism of PSA on CO_2 emissions by constructing dynamic spatial Durbin model and intermediary effect model. Furthermore, the dynamic threshold model is used to analyze the nonlinear characteristics between PSA and CO_2 emissions under different degrees of government intervention. The results show that: (1) overall, China's CO_2 emissions are path-dependent in the time dimension, showing a "snowball effect." PSA significantly inhibits CO_2 emissions in local city and the adjacent areas through the spatial spillover effect. (2) Heterogeneity analysis shows that there are significant differences in the impact of PSA on China's CO_2 emissions in different regions, time nodes, and sub-divided industries. PSA significantly inhibits CO_2 emissions in the eastern region, whereas considerably promotes CO_2 emissions in the central and western regions. In the two stages before and after that issued by the State Council in 2014, the impact of PSA on CO_2 emissions changes from being insignificant to significant inhibition. Besides, there are differences in the impact of sub-industry agglomeration of producer services on CO_2 emissions. The agglomerations of the industries at the low end of the value chain intensify the CO_2 emissions, whereas those at the high end of the value chain reduce CO_2 emissions. (3) The transmission mechanism test shows that PSA can indirectly inhibit CO_2 emissions through economies of scale, industrial structure upgrading, and technological innovation, among which technological innovation effect is leading first, followed by economies of scale and industrial structure. (4) The threshold effect shows that PSA has an obvious double-threshold effect on China's CO_2 emissions under the different levels of government intervention. When the level of government intervention is low, PSA inhibits CO_2 emissions; with the increase of the level of government intervention, the impact of PSA on CO_2 emissions changes from inhibition to promotion.

Accordingly, this paper put forward the policy implications:

1. The local governments should increase support for producer services. On the one hand, they can promote the networked and intensive development of producer services through financial support, planning and layout, and government guidance. On the other hand, they should accelerate regional integration, encourage governments at all levels to strengthen exchanges and cooperation, break the institutional barriers to factor flow, guide the rational and free flow of innovation factors, and improve

the allocation efficiency of innovation factors, giving full play to the promotion effect of PSA on CO_2 emission reduction in a larger space.

2. The local government should dynamically adjust industrial policies and take differential emission reduction measures in regions. The eastern region should make full use of the advantage of capital and talents, improve the efficiency of scientific and technological innovation, and create a diverse productive service function. The central and western regions should build a communication bridge to learn advanced technologies and ideas, break the restrictions on the development of local protectionism and producer services, and accelerate the spillover of technological innovation and the diffusion of knowledge. Particularly, the western region should give full play to its comparative advantages in policies, resources, and labor force and actively participate in technical exchanges and cooperation with the eastern and central regions. In addition, in adjusting the structure and mode, all regions should further promote the effective embedding of producer services in the manufacturing value chain and improve the development scale and speed of producer services, especially high-end producer services.
3. Local governments should take a moderate intervention on PSA development. On one hand, they should provide policy guarantees and financial supports for the all-around development of PAS, such as providing preferential tax policies, improving public service facilities, strengthening the training, and introducing high-end talents. On the other hand, local governments should avoid excessive intervention. They should adhere to promoting market-oriented reform. In formulating industrial development policies, they should jointly deploy inter-industry cooperation and market-oriented reform, follow the law of industrial development, and take the regional resource endowment, urban positioning and comparative advantage as the guidance, and thus decreasing resource misallocation and CO_2 emissions.

Although this study has systematically examined the impact of PSA on CO_2 emissions and the transmission mechanism, there are some limitations. This paper only takes the government intervention as the threshold variable to investigate the nonlinear characteristics between PSA and CO_2 emissions. There may be more factors affecting the nonlinear relationship, such as marketization, urbanization, and so on, which deserves to be further explored in future research.

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