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Does industrial collaborative agglomeration improve environmental efficiency? Insights from China's population structure

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Abstract: It is the theme of today to develop green economy and improve environmental efficiency (EE). As a comprehensive index to measure energy input, economic output and environmental development, environmental efficiency (EE) is of great significance for China to realize the sustainable development of economy and environment. China is in a critical period of industrial transformation and upgrading and ecological civilization construction, the effect of the collaborative agglomeration of manufacturing and productive services on environmental efficiency has drawn attention from policymakers. In this study, the stochastic frontier approach (SFA) with unpaid input is used to measure the environmental efficiency (EE) of 66 cities in eastern China during 2009-2018. Population structure is regarded as a mediator to investigate the impact of industrial collaborative agglomeration on environmental efficiency based on the spatial econometric model. The results show that industrial collaborative agglomeration has a positive impact on environmental efficiency, which can be moderated by population density, aging and quality at the same time, while the moderating effect of population urbanization is not significant. Therefore, it is necessary to optimize the coordinated governance system of regional ecological environment, accelerate the construction of industrial collaborative agglomeration, and promote the sustainable development of industry and ecology with the advantage of population structure in order to improve environmental efficiency (EE).

Keywords: environmental efficiency; industrial collaborative agglomeration; spatial analysis; pollution control; population structure

1 Introduction

Energy consumption and greenhouse gas emissions are not only the main reasons restricting the construction of ecological civilization in China, but also important problems in the sustainable development of economy and environment (Zhang and Da, 2013; Zhang and Da, 2015). In recent years, China has firmly ranked the second largest economy in the world by virtue of the steady economic development trend of 9.7% average annual growth rate of GDP (Han et al., 2018). However, with the rapid development of urbanization and industrialization, China is inevitably faced with problems such as the depletion of mineral energy, excessive deforestation of forest resources and haze pollution, which have seriously affected the health of residents and high-quality economic development (Yang et al., 2017; Yang et al., 2019; Chen et al., 2018; Song et al., 2020). In 2018, China had contributed 24% of the world's energy consumption and accounted for 27.6% of global carbon dioxide emissions, which demonstrates that China has become the main source of the growth of global energy demand and carbon emissions (B.P., 2019). China, a necessary element of global economy, was provided with the important responsibility to set an example in maintaining global sustainable development. Especially in the post-epidemic era, adhering to the concept of green development, which corresponds to the meaning of

community of shared future for mankind, and also shows the important role China plays in global sustainable development (Xi, 2017). Therefore, the Environmental Protection Law was revised and implemented in 2014 (MEE, 2018), in which the target of achieving carbon-neutral by 2060 was proposed. Whilst it is important to continuously introduce regulations and implement eco-environmental policies, it is more important to ensure that these invested efforts and resources are effective, namely, whether environmental efficiency is improved (Zhang, et al., 2019).

Traditional production efficiency is measured by the ratio of economic output to labor and capital input (Walker, et al., 2020), ignoring the negative impact of energy consumption and pollution emissions on the environment. While environmental efficiency is considered as an important means to measure economic, environmental performance and their interaction, which brings economic output into the research framework of ecological sustainable development and solves the problems of energy constraints and pollution emissions restrictions (Amigues and Moreaux, 2019). In addition, as a high energy consumption industry and the core driving force of China's economic growth, the manufacturing industry contributed 1.6% of the economic growth rate in National Bureau of Statistics of China (2020). At present, China is in the phase of industrial transformation and upgrading, and the changing of industries' forms and the relationships must have a further impact on environmental efficiency (Chen and Jia, 2017; He et al., 2018; Zhang, et al., 2019). Based on "made in China 2025" strategic plan, Chinese government clearly proposed that it is necessary to get rid of the reliance on the extensive traditional development mode with high energy consumption and low efficiency, and then promote the green transformation and upgrading of industries focusing on energy conservation and emission reduction (Yuan et al., 2019). For government, the main way of optimizing the allocation of resources and promoting green economy is to build up industrial agglomeration areas, among which the eastern coastal areas of China are the first to reduce energy consumption and pollutant emission by making the use of manufacturing agglomeration and taking industrial parks and development zones as carriers, in order to achieve high-quality economic growth. However, with the deepening of regional industrial division of labor, producer services have formed a forward spillover and backward incentive to the manufacturing industry because of its high value-added characteristics, resulting in a closer relationship between manufacturing and producer services. Industrial transformation and upgrading tends to infiltrate and coordinate the development of producer services in the manufacturing industry, and then industrial collaborative agglomeration has become a new pattern of regional industrial interconnected development (Gao and Li, 2011). At the same time, China is in a critical period of demographic transformation. From the perspective of population spatial structure, the construction of new-type urbanization, in the basis of the coordination of industrial development and ecological economy, is progressing steadily, which it is expected that by 2050, China's urbanization rate will exceed 80%. From the perspective of population age structure, people who are over 65 accounts for 11%, which ranks 10th in the world. The development trend of aging will inevitably affect the adjustment of industrial structure and the output of carbon emissions (Neill et al., 2010). From the perspective of population cultural structure, the central cities gradually relax the settlement policy and give preferential treatment, in order to introduce highly educated talents, and promote the cross-regional mobility. From the perspective of population distribution structure, the central city attracts more and more labor force by virtue of the perfect industrial chain layout, which increases the population density of the central city. Population structure, such as population density, population aging, population urbanization and population quality, plays a strong role in restricting and guiding the sustainable

development of industrial collaborative agglomeration (Golley and Zheng, 2015). Therefore, based on the concept of green development, this study analyzes the impact of industrial collaborative agglomeration on environmental efficiency, as well as the moderating effect of population structure in this process.

The marginal contributions of this study lie in the following aspects: (1) The theoretical framework of industrial collaborative agglomeration, population structure and environmental efficiency is put forward, and the action mechanism among them is discussed in detail. According to the characteristics of China's population structure, the population structure is subdivided into population density, population aging, population urbanization and population quality. Considering the representativeness of the development of urban industrial clusters in eastern China, this study makes an empirical test of the framework by using the panel data of eastern Chinese cities during 2009-2018. (2) The time distances are shortened between cities by the construction of China's high-speed train, even if the geographical distance between regions remains the same. The flow of resource factors and green technology spillovers are also accelerated. Therefore, in this study, the spatial econometric model based on time distance matrix is used to investigate the spatial correlation among variables so as to further refine the effect of factor resources on environmental efficiency. (3) It estimates the environmental efficiency under both economic output and energy constraints based on the stochastic frontier approach (SFA), putting the pollutants into the index system as unpaid input, which would be of great significance for the overall coordination between energy use and ecological construction.

The other sections are organized as follows: Section 2 shows literature review and research hypotheses. Section 3 introduces the research design, including data, methods and variable selection. Section 4 gives the empirical results and related analysis. Section 5 is the conclusion, policy enlightenment and research limitations.

2 Literature review and research hypotheses

(1) Industrial collaborative agglomeration and environmental efficiency

According to the theory of new economic geography, industrial collaborative agglomeration may have two aspects of influences on environmental efficiency. On one hand, the manufacturing industry can obtain cost surplus and income surplus by relying on the business convenience externalities and technological externalities provided by producer services agglomeration (Yang et al., 2016). Moreover, through vertical and horizontal multi-level correlation between manufacturing and producer services, which strengthening the efficiency of resource factor allocation can promote the spillover of knowledge and technology (Ben Arfi et al., 2018). Thus, improving energy efficiency and reducing pollution emissions on the basis of inter-industry correlation effect, which will form a virtuous circle system of industry-economy-environment (Shi and Shen, 2013). Furthermore, industrial collaborative agglomeration plays a role in promoting the environmental efficiency, which respectively rely on realizing specialized division of labor by attracting large-scale labor resources, improving labor productivity by means of skill training, and further optimizing the output efficiency of enterprises upstream and downstream of the industrial chain (Wang et al., 2018). Further, high-quality industrial parks attract more technical and management talents, which will promote industrial coordination and agglomeration of internal scientific and technological innovation capabilities. The research and development of green processes and environmental protection technologies allocated more funds, based on constant output, lower energy consumption and resource misallocation rate. Especially, industrial

collaborative agglomeration boosts the circular economy by utilizing the characteristics of related agglomeration among industries, which will help to reduce the unit pollution control cost of enterprises and fundamentally achieve the target of energy saving and emission reduction (Cheng, 2016). Finally, with the rapid increase in the scale and population density of the agglomerate area, residents will put forward higher requirements for environmental quality, due to the consideration of high-quality life. Not only advocating green emission reduction activities in their daily life, but also putting pressure on environmental regulatory departments to ensure the quality of ecological environment with strict environmental laws and regulations (Wang and Yu, 2017).

On the other hand, in order to rapidly form the agglomeration scale, the industrial subjects in the agglomeration area over-develop ecological resources and energy, intensive industrial emissions lead to environmental deterioration (Yuan and Xie, 2015; WierzBowski et al., 2017; Shen et al., 2018), and energy consumption further aggravate air pollution such as haze phenomenon (Wang et al., 2019). In addition, the local government may lower environmental and pollution standards in order to attract more foreign investment in the industrial area, which leads the agglomeration area to become a pollution haven (Liu et al., 2017). Similarly, enterprises in the agglomeration area face the limitation of market capacity due to the continuous expansion of the agglomeration scale, resulting in crowding effect and vicious competition for limited factor energy (Liu et al., 2017). Besides, enterprises in some agglomeration areas even take free-riding behavior rather than making contribution to improve the environment (Chen et al., 2018). Excessive pollution emissions exceed the endurance of the ecological environment and lead the environment deteriorate continuously. The researchers confirmed similar conclusions with Chinese inter-provincial panel data (Wang et al., 2019; Lan et al., 2020).

From the foregoing, industrial collaborative agglomeration has environmental externalities, but it is still unknown whether the environmental externalities in line with China's industrial collaborative agglomeration are positive or negative. We propose Hypothesis 1.

Hypothesis 1. Industrial collaborative agglomeration positively associates with environmental efficiency.

(2) Industrial collaborative agglomeration, population structure, and environmental efficiency

Next, we plug population structure into the analysis to briefly illustrate the moderating effect, in which the population structure is divided into four aspects: population distribution structure, population age structure, population spatial structure and population cultural structure, respectively.

The first is population distribution structure. The coordinated development of population density and industrial agglomeration areas is an important support for regional economic growth and high-quality development. Currently, the increase in population density in the region directly promotes the increase in the labor supply and the diversity of social labor. In particular, the enterprises of the upstream and downstream industries actively promote various innovative activities and constantly expand market capacity through the development and utilization of natural resources, resulting in friction between industrial development and environmental protection in a short term. Likewise, the increase in population density can promote the production lines of relevant enterprises in the industry to make full use of deployment, and concentrate the transmission of raw materials and energy, which is conducive to saving space and improving compactness. To a certain extent, this can reduce the energy cost of regional operation through infrastructure sharing.

The second aspect is population age structure. Demographic dividend is considered to be the

cornerstone of the development of China's manufacturing industry, but the turning point of the disappearance of demographic dividend has come with the increasing trend of aging. It directly results in a sharp decline of highly qualified and skilled labor force, which restricts the development of industrial agglomeration areas and industrial transformation and upgrading, thus hardly achieve sustainable economic development (Neill et al., 2010). On the other hand, the increasing aging population reduced the demand for high-energy consuming goods and activities such as private cars, which led to changes in the main structure of economic and social production and consumption, and then reduce the per-capita energy consumption of the society. Meanwhile, it can further develop the tertiary industry meeting the needs of the elderly, and fundamentally promote the optimization of the internal technological structure of the manufacturing and production services. Besides, considering the realistic background of environmental constraints and resource shortage, enterprises also invest more R&D funds in energy conservation and emission reduction in order to eliminate backward production capacity and also improve environmental efficiency (Lee and Mason, 2010).

The third is population spatial structure. The construction of new-type urbanization has a great impact on China's industrial layout, in which promoting the citizenization of agricultural transfer population is the primary task of China's new-type urbanization construction. It not only makes full use of the labor force transferred from agriculture and industry, but also promotes the rapid development of modern producer services and its collaborative agglomeration model with manufacturing industry. Therefore, it enhances the employment elasticity of industrial development. Specifically, relying on the advantages of industrial characteristics in small towns, the skill training and industrial undertaking capacity of the rural labor force have been strengthened. In particular, it promotes the development of alternative industries in resource-exhausted cities, such as fostering and strengthening the development of information technology and new energy industries, and gradually form a green economy development model oriented the cultivation of high-end industries.

The fourth is population cultural structure. As we all know, strengthening the transformation of green scientific and technological achievements is the key to promote the positive impact of industrial collaborative agglomeration of environmental efficiency. The improvement of population quality can ameliorate environmental efficiency by playing a positive role in the acceleration of knowledge mobility and technological complementarity between manufacturing and producer services. Furthermore, cities implement the policies to gather high-tech and educated talents, then deeply integrate talents chain and industry chain in order to transform tradition manufacturing to green, intelligent and high-end. Meanwhile, they encourage the research and development of low-carbon technologies and strengthen the efficiency of clean energy in the development of coordinated industrial agglomeration, comprehensively achieve a green system based on resource conservation and recycling, and fundamentally improve environmental efficiency. Based on the above analysis, we propose Hypothesis 2, 3, 4 and 5. The conceptual framework of this study is presented as Fig. 1.

Hypothesis 2. population density can positively moderate the effect of industrial collaborative agglomeration on environmental efficiency.

Hypothesis 3. population aging can positively moderate the effect of industrial collaborative agglomeration on environmental efficiency.

Hypothesis 4. population urbanization can positively moderate the effect of industrial collaborative agglomeration on environmental efficiency.

Hypothesis 5. population quality can positively moderate the effect of industrial collaborative agglomeration on environmental efficiency.

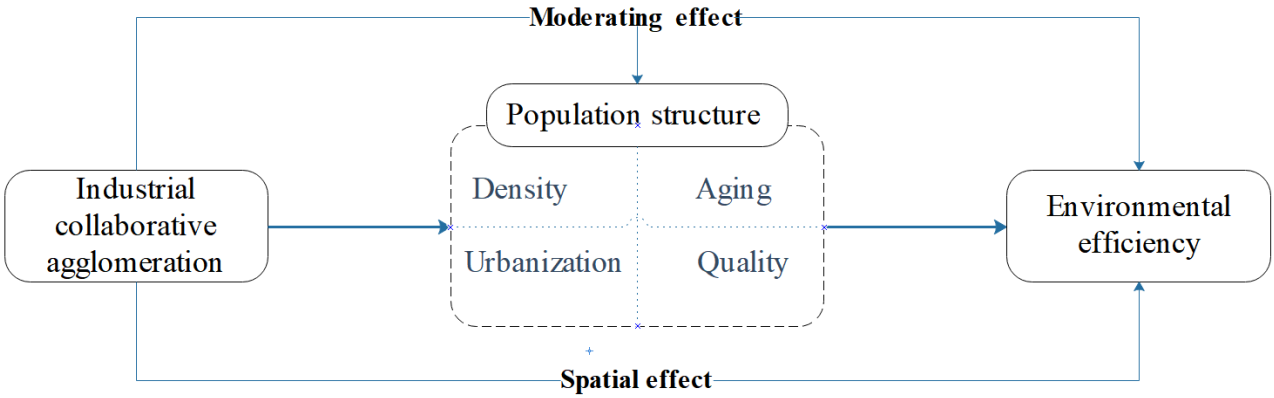

Fig.1. Conceptual framework of this study

3 Research Design

3.1 Data Sources

Eastern cities in China are the core areas of economic development, which are the first to promote the transformation of single-production manufacturing to "production + service". The coordinated agglomeration of manufacturing and producer services in the region is significant. In the period of 2009–2018, there are 66 prefecture-level cities with a growth rate of more than 6% in eastern China according to the experimental data of the 2018 GDP growth. The data are derived from the China City Statistical Yearbook and Statistical yearbook of each province. Individual missing data were filled by interpolation. In order to alleviate the problems of heteroscedasticity and multicollinearity, the related variables are logarithmically processed in this paper.

3.2 Variable Measurement

(1) Independent variable

By referring the previous studies and the difference of economic activity agglomeration index, the collaborative agglomeration characteristics of manufacturing industry and producer services are described (Zhang et al., 2017; Li et al.,2019). It is shown below.

$$LQ_{agcoo} = \left(1 - \frac{\left|LQ_{agman} - LQ_{agser}\right|}{LQ_{agman} + LQ_{agser}}\right) + \left|LQ_{agman} + LQ_{agser}\right| \qquad (1)$$

where LQagcoo describes the collaborative agglomeration index of manufacturing and producer services industry, LQagman denotes the index of manufacturing industry agglomeration, and LQagser is the producer services industry agglomeration index, both the LQagman and LQagser are calculated by location entropy index. In particular, refer to the classification principles of producer services (2019) issued by the National Bureau of Statistics and the general principles of academic research (Waiengnier et al., 2019; Xie et al., 2019; Yang et al., 2020), "wholesale and retail industry", "transportation, warehousing and postal industry", "information transmission, computer services and software industry ", "financial industry", "leasing and business services industry", "scientific research, technical services and geological exploration industry" comprise the producer service industry.

Additionally, the first item on the right side of the equation represents the quality of the co-agglomeration index, and the second one is the depth of the co-agglomeration index, so the index can

reflect the "collaborative quality" and "synergy height" at the same time, so as to fully reflect the level of collaborative agglomeration. The larger the industrial collaborative agglomeration index is, the smaller the difference between urban industries is, the higher the degree of collaborative agglomeration is, and vice versa.

(2) Dependent variable

The measurement of environmental efficiency involves many aspects, such as resource input, pollution output, economic development and so on. There are two streams of research methods: firstly, pollution emission is considered as the same as capital and labor factor at the beginning, which belong to the input factors affecting the environment. In fact, pollution emission is a kind of unpaid input (Ramanathan 2005); Secondly, taking major pollution emissions as undesirable output in a directional distance function model (Yuan et al., 2020). In this study, we adopt the first method to treat pollution emissions as input factors, and consider the stochastic frontier approach (SFA) as the technical efficiency which using the conditional expectation of the technical inefficiency rate term, based on the production function to construct the frontier. The results are less affected by the special points and will not have the same efficiency value, so the reliability and comparability of the efficiency measure are much better than the nonparametric frontier efficiency analysis value and it can be expressed as Eq. (2). The input-output variables in SFA are displayed in Table 1. The average value of industrial collaborative agglomeration and environmental efficiency during 2009-2018 are presented in Fig. 2.

$$Y_{it} = f(x_{it}, \beta)\exp(v_{it})\exp(-u_{it}), \qquad i = 1, \cdots, N \tag{2}$$

where Y_{it} and x_{it} represent output and input of the i decision-making unit during the t period, respectively. β is the model parameter. The random disturbance term is divided into two parts: v_i represents the statistical error, also known as the random error term; the other $u_{it} = u_i \exp(-\eta(t-T))$ represents the inefficiency of the technology, also known as the non-negative error term, η is the estimated parameter.

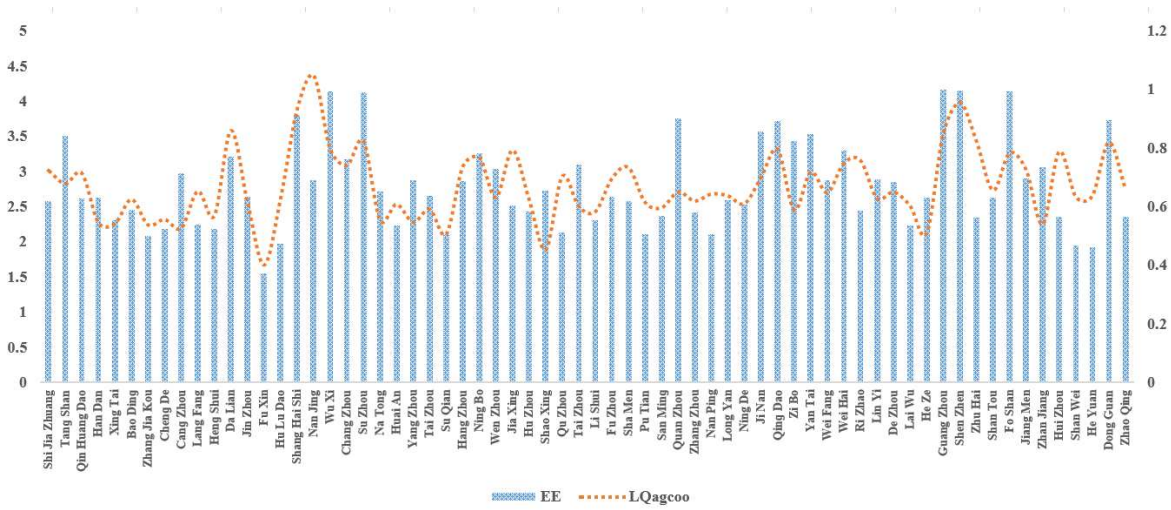

Fig. 2. The average value of industrial collaborative agglomeration and environmental efficiency during 2009-2018

Table 1 Input-output factors definition

Type	Index	Definition and description (unit)
Paid input	Labor force（L）	Number of employees at the end of a year in the total city（Million people）
	Capital stock（K）	Considering the earlier the selection of the base year, the smaller the influence of the error of the estimation of the capital stock of the base year on the subsequent years, so the base period for calculating the capital stock of each city is 1996, and the "perpetual inventory method" is used to estimate the capital stock data of each city（Million yuan）
	Energy（E）	Electric power consumption data are automatically recorded by watt-hour meter instruments, which eliminates subjective interference, and there is a high correlation between electric power consumption and energy consumption（104Kilowatt-hour）
Unpaid input	Soot（D）	Industrial soot emissions in the total city（Ton）
	SO2（S）	Industrial sulfur dioxide emissions in the total city（Ton）
	Waste water（W）	Industrial waste water discharge in the total city（104 ton）
Desirable output	GDP（Y）	Actual GDP of prefecture-level cities with constant price in 2009（Million yuan）

(3) Moderating variable

In order to explore the moderating effect of population structure in the process of industrial collaborative agglomeration on environmental efficiency, the population structure (*PS*) is divided into four angles: population distribution structure, population age structure, population spatial structure and population cultural structure. We further refine it into four indicators: population density (*PD*), population aging (*PG)*, population urbanization (*PU*) and population quality (*PQ*). Population density (*PD*) is estimated by the logarithmic value of the ratio of the city's total population to its administrative area at the end of the year. Due to the missing data of urban aging population, population aging (*PG*) is characterized inversely by the natural growth rate of urban population. With the increase of natural population growth rate and the increase of population base, the proportion of aging population will decrease, that is, they have the opposite trend. The ratio of the natural increase in population (the number of births minus the number of deaths) to the average total population in one year. And the data are normalized to ensure the comparability of index evaluation. Population urbanization (*PU*) is characterized by the logarithm of the ratio of the urban population to the total urban population. Population quality (*PQ*) is estimated by the logarithm of the number of full-time teachers per 10000 people in the city (Xu et al., 2020).

(4) Control variables

To control the other factors affecting environmental efficiency: government intervention degree, industrial structure, environmental regulation, the degree of opening to the outside world and infrastructure are selected as the control variables. Government intervention degree (GOV), which is measured by the ratio of the public budgets to the gross regional product. Industrial structure (IS) is

represented by the ratio of Tertiary Industry as Percentage to GRP. Environmental regulation (ER) is comprehensively measured by adopting entropy method with emissions of soot, so2 and waste water (Yang et al., 2015). The degree of opening to the outside world (OPEN), which is measured by the amount of foreign capital actually utilized and converted to the RMB by the midpoint of the exchange rate of RMB against the US dollar announced by the China Bureau of Statistics. Infrastructure level (FUND), which is measured by the proportion of investment in fixed assets in the year as a percentage of gross regional product. Square term of industrial collaborative agglomeration (LQagcoo2) represents the nonlinear relationship between industrial collaborative agglomeration and environmental efficiency. The descriptive statistics of variables in the study are summarized in Table 2 and the correlation coefficients of variables are shown as Table 3.

Table 2 Descriptive statistics

variables	Observations	mean	std. dev	max	min
EI	660	0.6713	0.1756	0.9989	0.0985
*ln*LQagcoo	660	1.0075	0.1954	2.6198	0.1231
*ln*PD	660	6.2650	0.6535	7.8816	4.5437
PG	660	0.4150	0.1087	1.0000	0.0000
*ln*PU	660	4.0654	0.2727	6.0064	2.9750
*ln*PQ	660	4.6001	0.2540	5.7038	4.1431
GOV	660	9.0417	4.4909	39.4324	3.3258
*ln*OPEN	660	12.9902	1.4526	16.3249	7.6680
*ln*FUND	660	4.1607	0.4977	6.3122	2.3535
*ln*IS	660	3.7476	0.1836	4.2732	3.3167
ER	660	0.3342	0.7322	8.0595	0.0002
*ln*LQagcoo^2	660	1.0533	0.4237	6.8632	0.0151

Table 3 Correlation coefficient of each variable

Variable	LQagcoo	EE	PD	PG	PU	PQ	GOV	IS	ER	OPEN	FUND
LQagcoo	1.000										
EE	0.445***	1.000									
PD	0.343***	0.436***	1.000								
PG	-0.024	-0.088**	0.080**	1.000							
PU	0.463***	0.305***	0.439***	-0.063	1.000						
PQ	0.540***	0.377***	0.376***	0.192***	0.619***	1.000					
GOV	0.143***	-0.130***	0.136***	-0.185***	0.310***	0.162***	1.000				
IS	0.362***	0.099**	0.390***	-0.108***	0.633***	0.525***	0.525***	1.000			
ER	0.140***	0.252***	0.121***	-0.081**	0.092**	0.064*	0.005	-0.006	1.000		
OPEN	0.525***	0.522***	0.511***	-0.149***	0.601***	0.515***	0.298***	0.501***	0.255***	1.000	
FUND	-0.326***	-0.535***	-0.358***	-0.005	-0.278***	-0.416***	0.306***	-0.166***	-0.064	-0.274***	1.000

Note: ***, ** and * respectively indicate that the parameter estimation is significant at the levels of 0.01, 0.05 and 0.1.

3.3 Spatial Econometric Model

In this study, the factors that may affect environmental efficiency include industrial collaborative agglomeration, population structure, economic development level, government intervention degree, the degree of opening to the outside world and infrastructure level. The population structure as moderating variable is divided into four aspects: population distribution structure, population age structure, population spatial structure and population cultural structure, which are measured by population density, population aging, population urbanization and population quality index respectively, and they may moderate the relationship between industrial collaborative agglomeration and environmental efficiency. Then, on the base of the augmented Cobb-Douglas production function model (Xie, 2013; Wu and Li, 2018), and in order to reduce the potential threat of multicollinearity, we center the interaction terms before incorporating them into the models (Aiken and West, 1991). The basic analysis model of this study is built as follows:

$$EE_{it} = c + \beta_1 LQagcoo_{it} + \beta_2 LnPD + \beta_3 LQ_{agcoo} * InPD + \beta_4 control_{it} + \varepsilon_{it} \quad (3)$$

$$EE_{it} = c + \beta_1 LQagcoo_{it} + \beta_2 LnPG + \beta_3 LQ_{agcoo} * InPG + \beta_4 control_{it} + \varepsilon_{it} \quad (4)$$

$$EE_{it} = c + \beta_1 LQagcoo_{it} + \beta_2 LnPU + \beta_3 LQ_{agcoo} * InPU + \beta_4 control_{it} + \varepsilon_{it} \quad (5)$$

$$EE_{it} = c + \beta_1 LQagcoo_{it} + \beta_2 PQ + \beta_3 LQ_{agcoo} * PQ + \beta_4 control_{it} + \varepsilon_{it} \quad (6)$$

where i and t denote region and time, respectively. β is the elasticity coefficient, and the ε_{it} is the error term.

The spatial panel econometric model is used to characterize the spatial correlation of research variables, which can more effectively study the impact of industrial collaborative agglomeration on environmental efficiency, and reflect the moderating effect of population structure changes on the relationship between them. According to the correlation among the variables, the spatial panel econometric model is divided into three categories: the spatial error model (SEM) focuses on the spatial correlation that exists in the error disturbance terms, namely, the degree to which the observations of a given region are affected by the adjacent regions through the errors of the dependent variables. The spatial lag model (SLM) considers the spatial correlation of dependent variables in different regions and calculates whether the variables have spillover effects. The spatial Durbin model (SDM) comprehensively takes into account the spatial error and lag among the variables, which has a more general form (Ren et al., 2010; Yang et al., 2017). In this study, a spatial panel model was constructed based on the conceptual model. The specific models are as follows:

$$Y_{it} = \beta(lnLQagcoo_{it} + control_{it}) + \lambda \sum_{j=1}^{N} W_{it} Y_{it} + \alpha \sum_{j=1}^{N} W_{it}(lnLQagcoo_{it} + control_{it}) + \mu_{it} \quad (7)$$

$$\mu_{it} = \rho w \mu + \varepsilon_{it} \quad (8)$$

To further test the moderating effects, we incorporate the moderators (LnPD, LnPG, LnPU and PQ) and the interaction terms (LQagcoo*InPD, LQagcoo*InPG, LQagcoo*InPU and LQagcoo*PQ) into separate regression models (see Models3, 4, 5 and 6).

$$Y_{it} = \beta(lnLQagcoo_{it} + lnPD_{it} + lnLQagcoo_{it} * lnPD_{it} + control_{it}) + \lambda \sum_{j=1}^{N} W_{it} Y_{it} + \alpha \sum_{j=1}^{N} W_{it}(LQagcoo_{it} + lnPD_{it} + lnLQagcoo_{it} * lnPD_{it} + control_{it}) + \mu_{it} \quad (9)$$

$$Y_{it} = \beta(lnLQagcoo_{it} - lnPG_{it} - lnLQagcoo_{it} * lnPG_{it} + control_{it}) + \lambda \sum_{j=1}^{N} W_{it} Y_{it} + \alpha \sum_{j=1}^{N} W_{it}(LQagcoo_{it} + lnPG_{it} + lnLQagcoo_{it} * lnPG_{it} + control_{it}) + \mu_{it} \quad (10)$$

$$Y_{it} = \beta(lnLQagcoo_{it} + lnPU_{it} + lnLQagcoo_{it} * lnPU_{it} + control_{it}) + \lambda \sum_{j=1}^{N} W_{it} Y_{it} + \alpha \sum_{j=1}^{N} W_{it}(LQagcoo_{it} + lnPU_{it} + lnLQagcoo_{it} * lnPU_{it} + control_{it}) + \mu_{it} \quad (11)$$

$$Y_{it} = \beta(lnLQagcoo_{it} + PQ_{it} + lnLQagcoo_{it} * PQ_{it} + control_{it}) + \lambda \sum_{j=1}^{N} W_{it} Y_{it} + \alpha \sum_{j=1}^{N} W_{it}(LQagcoo_{it} + PQ_{it} + lnLQagcoo_{it} * PQ_{it} + control_{it}) + \mu_{it} \quad (12)$$

Where Y_{it} denotes environmental efficiency of each region, i and t denote region and time, respectively. $\lambda W_{it} Y_{it}$ is the spatial lag term of the dependent variable, and $\alpha W_{it} X_{it}$ is the spatial lag term of the independent variable and control variables. β is the regression coefficient of the explanatory variable, and λ is the regression coefficient of the independent variable. α and ρ are the spatial regression coefficient and the spatial error regression coefficient, respectively. When $\lambda \neq 0$ and $\alpha = 0$, the SLM is used. When $\rho \neq 0$, $\lambda = 0$, and $\alpha = 0$, the SEM is used. When $\lambda \neq 0$, $\alpha \neq 0$, and $\rho = 0$, the SDM is used. Moreover, W_{ij} is the spatial weight matrix of order n. ε_{it} and u_{it} are the random error terms subject to normal distribution.

3.4 Time Distance Weight Matrix

With the construction and development of China's high-speed railway, the geographical distance between regions remains unchanged, but the improvement of vehicle speed shortens the time distance and frequent convergence of factor resources, which provides a more convenient channel for knowledge spillover, especially tacit knowledge spillover, and promotes intra-regional industrial collaborative agglomeration and inter-regional industrial complementarity. This study calculates the shortest mileage of high-speed rail lines between two cities in eastern China, based on the first law of geography and China's high-speed rail network. Considering that China's high-speed railway has a designed top speed

of 350 km/h, but it is difficult to achieve the ideal operation condition continuously, the speed is set to 300 km/h between provincial capitals, 250 km/h between provincial capitals and non-provincial capitals, and 200 km/h between non-provincial capitals. In addition, the influence of neighbor explanatory variables may be exaggerated simply by using the time distance weight matrix due to the large number of cities. Therefore, time distance matrixthe weight matrix of time distance attenuation based on the reciprocal of time distance square instead of the time distance weight matrix to represent the spatial relationship of the city. That is:

$$W_{ij} = \begin{cases} 1/time^2_{ij}, i \neq j \\ 0 \quad\quad\quad, i = j \end{cases} \tag{13}$$

4 Empirical Research and Analysis

4.1 Spatial Auto-correlation Test

The spatial correlation between industrial collaborative agglomeration and environmental efficiency refers to the spillover and diffusion effects of industrial factor flow and pollution control between adjacent regions. The spatial correlation can be determined by calculating the spatial auto-correlation coefficient, the global Moran’s index, which is used to measure the spatial correlation, reflect the similarity of the spatial adjacency of elements or the attribute values of regional units adjacent to the space. The calculation formula for the global Moran’s index is as follows (Wang, et al., 2017)

$$I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\sum_{k=1}^{n}(x_k - \bar{x})^2} = \frac{\sum_{i=1}^{n}\sum_{j\neq i}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{S^2\sum_{i=1}^{n}\sum_{j\neq i}^{n} w_{ij}} \tag{14}$$

where w_{ij} denotes the spatial weight. n denotes the total number of regions. x_i and x_j represent the observed values of region i and region j respectively. $\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i$ refers to the average value of the observed indicators, and $S^2 = \frac{1}{n}\sum_i (x_i - \bar{x})^2$ is the variance of the observed indicators.

The range of the global Moran’s index is from -1 to 1. If the value is closer to 1, the difference of inter-regional observations is smaller or the distribution of elements tends to more agglomerate, showing a positive spatial correlation. The contrary is opposite. If it is closer to -1, the difference of inter-regional observations is greater or the distribution of elements tends to be discrete, showing a spatial negative correlation. A value close to 0 indicates random distribution or no spatial auto-correlation (Xu and Deng, 2012).

This study uses Moran scatter plot to analyze the local spatial autocorrelation, and further examines the distribution pattern of industrial collaborative agglomeration and environmental efficiency. The horizontal axis of Moran scatter chart is the correlation variable x , and the vertical axis is its spatial

lag vector w_x, which is represented by a visual two-dimensional graph with (w_x, x) as the coordinate point and is often used to study the local spatial instability.

In the Moran scatter plot, the observations in different quadrants have different agglomeration types, in which when the scatter points are distributed in the first quadrant and the third quadrant, they show high-high and low-low agglomeration types, showing a positive spatial correlation, which means that the attributes of the spatial unit are similar to those of the adjacent elements. When the scattered points are distributed in the second quadrant and the fourth quadrant, they are shown as high-low and low-high agglomeration types, showing a negative spatial correlation, namely, the attributes of the spatial unit are not similar to those of the adjacent units.

The global Moran's index and Moran scatter plot are given in Table 4 and Fig. 3, respectively. Table 4 shows that there is a significant spatial positive correlation between industrial collaborative agglomeration and environmental efficiency, and the global spatial correlation between them is increasing from 2009 to 2018. Fig. 3 shows that the number of scatter values of industrial collaborative agglomeration and environmental efficiency in the first quadrant (high-high) and the third quadrant (low-low) are more than those in the second quadrant (high-low) and the fourth quadrant (low-high), indicating that the spatial positive spillover effect makes the agglomeration degree of the adjacent units tend to be similar and strengthen, which further confirms the calculation results of the Moran index. With the passage of time, the points of the second and fourth quadrants tend to transfer to the first and third quadrants, indicating that the development of regional elements is affected by the positive spillover of the attributes of adjacent spatial units, and the cooperative change trend between them is significant. Therefore, spatial regression analysis is necessary.

Table 4 Spatial autocorrelation statistics on industrial collaborative agglomeration and environmental efficiency

Year	*LQagcoo Moran's I*	*EE Moran's I*
2009	0.012463	0.130603**
2010	0.223476***	0.134442**
2011	0.224695***	0.122103**
2012	0.278543***	0.129087**
2013	0.292383***	0.154392***
2014	0.29942***	0.159928***
2015	0.288456***	0.164193***
2016	0.322783***	0.177534***
2017	0.340728***	0.190371***
2018	0.374408***	0.199178***

Note: "***", "**", "*" indicate that they passed the test at the significant levels of 1%, 5%, and 10%, respectively.

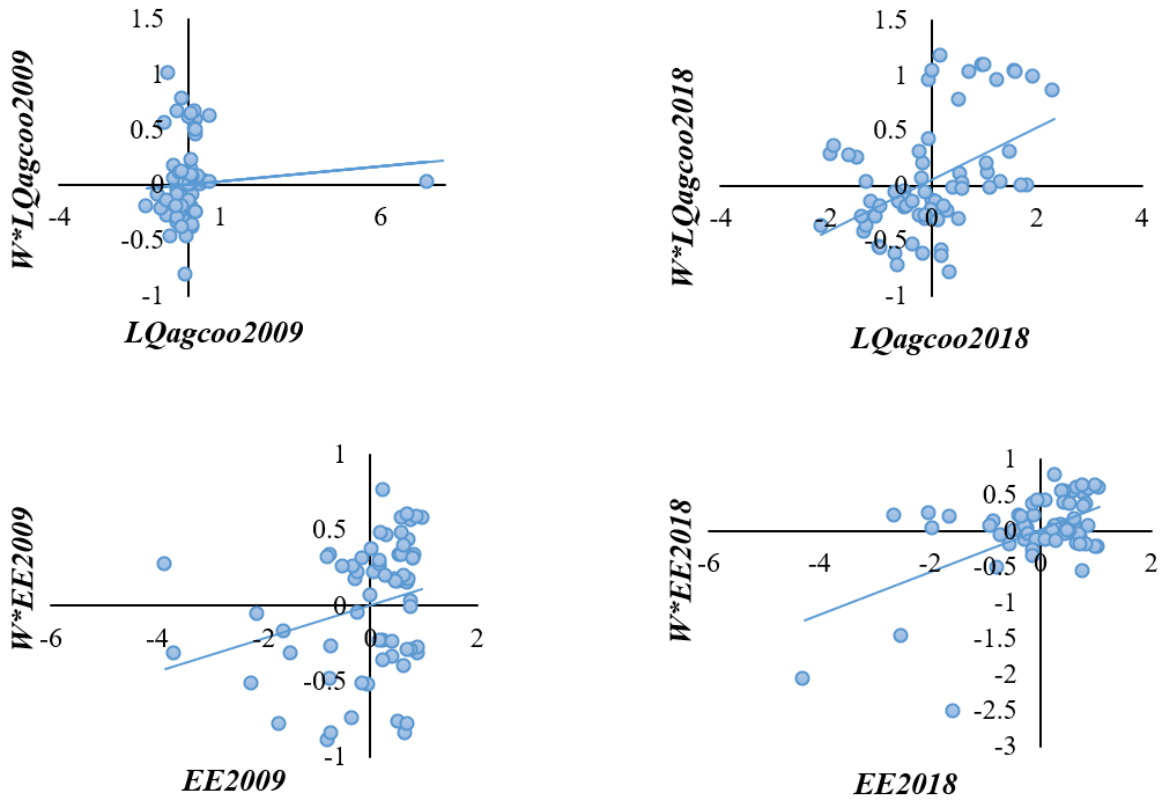

Fig. 3. The Moran scatter plot of industrial collaborative agglomeration and environmental efficiency

4.2 Analysis of Regression Results

Choosing the appropriate spatial econometric model is directly related to the accuracy of the measurement results among variables. According to Elhorst's method (Elhorst et al., 2012), the spatial econometric model is tested by the combination of "special to general" and "general to special". According to the test idea from "special to general", we conduct the models without spatial interaction effects and employ Lagrange Multiplier (LMLAG and LMERR) and its robustness (Robust-LMLAG and Robust-LMERR) tests for the spatial error model (SEM) and the spatial lag model (SLM) estimators. If LMLAG is more statistically significant than LMERR, SLM is selected. While if LMERR is more statistically significant than LMLAG, SEM is selected. If both LMLAG and LMERR pass the significance test, it is necessary to further compare the results of R-LMLAG and R-LMERR tests.

Table 5 presents the estimation results for the non-spatial econometric models: pooled OLS only, spatial fixed effects only, time-period fixed effects only and spatial and time-period fixed effects, respectively. LR test is conducted to examine the null hypothesis that the spatial effects and time-period effects are jointly non-significant. The null hypothesis that the spatial fixed effects are jointly non-significant is rejected at 1% significance level (69.2552, $p<0.01$), and the null hypothesis that the time-period fixed effects are jointly non-significant is rejected (77.2960, $p<0.01$). Therefore, these results prove the rationality of the panel data model with spatial fixed effects and time-period fixed effects. To examine the type of spatial effects model, the LM test and robust LM test are carried out on the endogenous spatial interaction effects and the error spatial interaction effects of the non-spatial panel model. The results are showed at the bottom of Table 6. For the LM test, the null hypothesis of no spatially lagged dependent variable and the null hypothesis of no spatially auto-correlated error term are rejected

at 1% significance level in all model specifications. With regard to the robustness test results, the null hypothesis of no spatially auto-correlated error term can be rejected at the 1% significance level in all model specifications, while the null hypothesis of no spatially lagged dependent variable cannot be rejected in pooled OLS and spatial fixed effects models, indicates R-LMERR is more statistically significant than R-LMLAG in all model specifications. Apparently, the results reflect that there is a strong spatial correlation among the data and the SEM is more consistent with the data in the study, so SEM and spatial Durbin model (SDM) should be taken into account.

Table 5 Regression results of the non-spatial panel model

variable	Pooled OLS	Spatial Fixed Effects	Time Period Fixed Effects	Spatial and Time Period Fixed Effects
Intercept	1.1394*** （7.4386）	—	—	—
lnLQagcoo	0.3487*** （3.6903）	0.3501*** （3.7470）	0.2923*** （3.1501）	0.2953*** （3.2258）
GOV	-0.0014 （-0.9465）	-0.0030** （-1.9808）	-0.0008 （-0.5270）	-0.0022 （-1.4912）
lnIS	-0.1732*** （-4.7481）	-0.1641*** （-4.5803）	-0.1722*** （-4.9329）	-0.1634*** （-4.7887）
ER	0.0267*** （3.8209）	0.0210*** （3.0441）	0.0303*** （4.1392）	0.0237*** （3.2658）
lnOPEN	0.0369*** （8.9286）	0.0398*** （9.7323）	0.0390*** （9.4398）	0.0418*** （10.2403）
lnFUND	-0.1387*** （-11.5520）	-0.1352*** （-11.4915）	-0.1508*** （-11.6023）	-0.1503*** （-11.6605）
$lnLQagcoo^2$	-0.0644 （-1.4854）	-0.0558 （-1.2986）	-0.0541 （-1.2853）	-0.0455 （-1.0948）
Log-L	434.5801	471.7290	467.7086	506.3566
LM-lag	100.1335***	95.2232***	64.8351***	58.5343***
(robust)	1.4923	0.9550	5.3029**	5.4417**
LM-error	142.2398***	140.5807***	70.3827***	62.0679***
(robust)	43.5986***	46.3124***	10.8505***	8.9754***

Note: The t value is in parentheses. “***”, “**”, “*” indicate that they passed the test at the significant levels of 1%, 5%, and 10%, respectively.

Table 6 Testing results of Wald-test and LR-test

Test	Statistics	P values
Wald spatial lag	70.4743	0.0000
Wald spatial error	54.7435	0.0000
LR spatial lag	73.1374	0.0000
LR spatial error	65.8504	0.0000

Next, according to the test idea of "general to special", if the non-spatial panel model based on these LM tests is rejected to support the spatial panel model. Then we investigate the spatial random effect SDM and the spatial fixed effect SDM by Hausman test, and the result (11.482, P=0.7177) indicates that

the SDM model with time-period fixed and spatial random should be chosen. To further determine the type of spatial effect, Wald test and LR test are used to decide whether SDM model can be simplified to SLM model (H0: $\gamma = 0$) or SEM model (H0: $\gamma+\rho\beta = 0$) (Burridge, 1981). If both tests point to the same single spatial interaction effect and also are consistent with LM test and robust LM test, SLM or SEM model will be adopted. If the test results are inconsistent or both of null hypothesis are rejected SDM model will be used. Table 6 shows that the null hypothesis of Wald test and LR test of SLM and SEM model is strongly rejected at the significance level of 1%, which means that SDM model is a more generalized and robust form comparing with SLM and SER. Therefore, this study chooses SDM model with time-period fixed and spatial random for regression analysis.

It is noteworthy that the coefficients of the SDM model do not directly reflect the marginal effects of the corresponding explanatory variables on the dependent variable (LeSage and Pace, 2010), we thus report the direct and indirect effects of the independent variables based on partial differential equation of formula (6), (8), (9), (10) and (11), respectively. The direct effect measures the influences caused by local region and the indirect effect evaluates the impacts of the neighboring regions. As shown at the bottom of Table 5, Moran index and spatial auto-correlation parameter λ are statistically significant at 1% level in all model specifications, which shows that the spatial econometric model can characterize the spatial linkage among variables. The results suggest that an increase in environmental efficiency of neighboring regions would cause the rising of that in the region. All the models in Table 7 show that the direct and indirect effects of industrial collaborative agglomeration on environmental efficiency are positive and significant at least the 5% level, in which the indirect effects are higher. Besides, the environmental efficiency is not only caused by the industrial collaborative agglomeration in the local region, but also heavily influenced by neighboring regions. H1 is thus supported. This finding is congruent with the arguments of Zeng et al. (2021) who have found that industrial collaborative agglomeration can augment the level of green innovation because of the improved market system (Zeng et al., 2021).

On one hand, regional economic integration strengthens the spatial complementarity of industrial layout between neighboring regions, which conduces to promote the producer service industry to embed green production technology and clean energy technology into all aspects of manufacturing production, and thus realizes the sharing of manpower, resources and technology. The higher level opening up to the world is, the higher efficiency of learning and absorbing foreign advanced green production processes, which further leads to the reduction of energy input intensity and pollution emission intensity of the manufacturing industry, and finally promotes the improvement of environmental efficiency through energy saving and emission reduction. On the other hand, there is competition and imitation behavior in the process of regional development caused by the high diffusivity and cross-regional spread of three pollution discharge which is closely related to environmental efficiency. Meanwhile, the implementation of clean and efficient environmental protection model and environmental regulation policy will form a strong demonstration effect on the neighboring regions. Then virtuous cycle mechanism with high environmental efficiency as the benchmark is gradually formed. The indirect effect of the square term coefficient of industrial collaborative agglomeration is statistically significant at 1% level, reflecting the nonlinear characteristics of the impact of industrial collaborative agglomeration in this region on environmental efficiency in neighboring regions. It is considered that there is a negative environmental externality of “free riding” behavior, which there may be transfer pollution emissions to neighboring areas without paying the bill (Monogan et al., 2017). The direct effects of Square term of industrial

collaborative agglomeration ($LQagcoo^2$) did not pass the significance test of all model specifications, indicating that there is no industrial over-agglomeration phenomenon.

Model (8) in Table 7 shows that industrial collaborative agglomeration and population density have significantly positive impacts on environmental efficiency, and the coefficients of them are 0.2915, 0.0723, respectively, both significant at 1% level. The coefficient of the interaction term of industrial collaborative agglomeration and population density is 0.0795, significant at 10% level, indicating population density can positively moderate the effect of industrial collaborative agglomeration on environmental efficiency. H2 is thus supported.

Model (9) in Table 7 examines the impacts of industrial collaborative agglomeration and population aging on environmental efficiency. The coefficient of population aging is -0.11, significant at 5% level, indicating the decline of population aging has a blocking effect on the improvement of environmental efficiency, which means the positive effect of population aging on environmental efficiency in the research period. The coefficient of the interaction term of industrial collaborative agglomeration and population aging is -0.5931, significant at 1% level, which proves that population aging has a positive moderating effect on the correlation between industrial collaborative agglomeration and environmental efficiency. H3 is also verified.

Relevant results of the moderating effect of population urbanization (PU) are shown in Model (10) in Table 7. The coefficient of industrial collaborative agglomeration and population urbanization are 0.2725 and 0.0412, and pass the significance levels of 1% and 10%, respectively. However, the coefficient of the interaction term PU*LQagcoo is 0.0535, positive but not significant, suggesting that population urbanization does not moderate the relation between industrial collaborative agglomeration and environmental efficiency, and H4 is not supported.

Model (11) presents the results concerning the impacts of industrial collaborative agglomeration, population quality and the interaction term of industrial collaborative agglomeration and population quality on environmental efficiency. The coefficient of population quality is 0.0263, positive but not significant, while the coefficient of the interaction term PQ*LQagcoo is 0.2588, significant at 10% level. This proves that population quality is an essential factor in promoting environmental efficiency by strengthening the promotion effect of industrial collaborative agglomeration. In other words, when population quality is observed in the economic development, industrial collaborative agglomeration and population quality can interaction efficiently, with a positive effect on environmental efficiency. H5 is evidenced.

Table 7 The estimation results of the moderating effect of population structure.

variable	(7)		(9)		(10)		(11)		(12)	
	direct effects	indirect effects	direct effects	Indirect effects	direct effects	indirect effects	direct effects	indirect effects	direct effects	indirect effects
lnLQagcoo	0.2551***	0.7257**	0.2915***	0.7466**	0.2147**	0.8784**	0.2725***	0.9889***	0.3759***	0.7541**
	(2.7053)	(2.0555)	(3.1988)	(1.9939)	(2.4069)	(2.5494)	(3.0158)	(2.6580)	(3.2569)	(2.0058)
lnPD/-PG/lnPU/lnPQ			0.0723***	-0.0680**	-0.1100**	-0.0360	0.0412*	-0.0014	0.0263	-0.1845*
			(7.1873)	(-2.4572)	(-2.2709)	(-0.2573)	(1.6943)	(-0.0195)	(0.6923)	(-1.7672)
*lnPD*lnLQagcoo*			0.0795*	-0.1668						
			(1.6926)	(-1.1639)						
*-PG*lnLQagcoo*					-0.5931***	-0.0603				
					(-2.7000)	(-0.1014)				
*lnPU*lnLQagcoo*							0.0535	0.0475		
							(0.9144)	(0.2655)		
*lnPQ*lnLQagcoo*									0.2588*	-0.3524
									(1.8308)	(-0.9891)
GOV	0.0012	-0.0229***	0.0015	-0.0209***	0.0023*	-0.0197***	0.0022	-0.0206***	0.0020	-0.0198***
	(0.8035)	(-4.5745)	(1.0809)	(-4.4313)	(1.6367)	(-4.1282)	(1.5767)	(-4.3786)	(1.4679)	(-4.1904)
lnIS	-0.2891***	0.6017***	-0.3427***	0.6287***	-0.2671***	0.5369***	-0.3149***	0.5682***	-0.3166***	0.6704***
	(-8.1338)	(5.7746)	(-10.0852)	(6.0324)	(-7.6242)	(5.4527)	(-8.2868)	(5.2455)	(-8.5696)	(6.2867)
ER	0.0209**	0.0004	0.0286***	-0.0080	0.0271***	-0.0008	0.0259***	0.0030	0.0267***	0.0022
	(2.4134)	(0.0163)	(3.5932)	(-0.3713)	(3.3608)	(-0.0377)	(3.1925)	(0.1417)	(3.3650)	(0.1089)
lnOPEN	0.0346***	0.0206	0.0252***	0.0200	0.0306***	0.0235*	0.0301***	0.0180	0.0324***	0.0260*
	(8.1484)	(1.5388)	(6.1815)	(1.4751)	(7.8235)	(1.8176)	(7.2453)	(1.3433)	(7.7868)	(1.8451)
lnFUND	-0.1557***	0.0194	-0.1366***	-0.0102	-0.1623***	0.0143	-0.1584***	0.0149	-0.1519***	-0.0166
	(-11.9115)	(0.4801)	(-10.8535)	(-0.2608)	(-12.9597)	(0.3608)	(-12.4360)	(0.3848)	(-12.2278)	(-0.4391)
$lnLQagcoo^2$	-0.0356	-0.4233**	-0.0725*	-0.3671*	-0.0402	-0.4792***	-0.0579	-0.5258***	-0.1112**	-0.3829**
	(-0.8401)	(-2.3790)	(-1.7253)	(-1.9134)	(-1.0113)	(-2.7896)	(-1.3902)	(-2.8205)	(-2.1040)	(-2.0476)
λ	0.4270***		0.4550***		0.4080***		0.4200***		0.4170***	
	(8.7954)		(9.7059)		(8.2708)		(8.6261)		(8.5698)	
R^2	0.6763		0.6656		0.6379		0.6345		0.6423	
log-likelihood	572.7651		559.8041		536.5424		532.7423		540.0212	
Moran's I	0.2120***		0.2375***		0.2107***		0.2087***		0.2450***	

Note: The t value is in parentheses. "***", "**", "*" indicate that they passed the test at the significant levels of 1%, 5%, and 10%, respectively.

Table 8 Robustness test of impact of industrial collaborative agglomeration on environmental efficiency

variable	(7)		(9)		(10)		(11)		(12)	
	direct effects	indirect effects	direct effects	Indirect effects	direct effects	indirect effects	direct effects	indirect effects	direct effects	indirect effects
lnLQagcoo	0.2480**	0.0525	0.2779***	0.2306	0.2104**	0.2899	0.2528***	0.2183	0.3601***	0.2013
	(2.5769)	(0.1640)	(3.0768)	(0.7118)	(2.3433)	(0.9701)	(2.7660)	(0.6449)	(3.2582)	(0.5820)
lnPD/-PG/lnPU/lnPQ			0.0726***	-0.0692**	-0.0999*	-0.0570	0.0367	-0.0138	0.0261	-0.2089**
			(7.4979)	(-2.4727)	(-1.9099)	(-0.3720)	(1.4238)	(-0.1626)	(0.6864)	(-2.0489)
*lnPD*lnLQagcoo*			0.0786*	-0.1726						
			(1.7821)	(-1.1110)						
*-PG*lnLQagcoo*					-0.5585**	-0.2414				
					(-2.4948)	(-0.3735)				
*lnPU*lnLQagcoo*							0.0464	-0.1451		
							(0.7911)	(-0.6003)		
*lnPQ*lnLQagcoo*									0.2591*	-0.4006
									(1.8031)	(-1.0802)
GOV	0.0006	-0.0305***	0.0013	-0.0271***	0.0021	-0.0252***	0.0020	-0.0274***	0.0016	-0.0267***
	(0.3980)	(-4.9799)	(0.9692)	(-4.7880)	(1.5299)	(-4.6073)	(1.3840)	(-5.1001)	(1.1156)	(-4.6125)
lnIS	-0.2842***	0.6338***	-0.3403***	0.6541***	-0.2643***	0.5371***	-0.3130***	0.6111***	-0.3144***	0.7418***
	(-8.0521)	(5.1567)	(-9.9878)	(5.4743)	(-7.4215)	(4.9561)	(-7.6877)	(5.0649)	(-8.3215)	(5.9406)
ER	0.0196**	-0.0053	0.0244***	-0.0080	0.0251***	-0.0010	0.0235***	0.0054	0.0243***	0.0025
	(2.3726)	(-0.2023)	(3.2906)	(-0.3268)	(3.2675)	(-0.0418)	(3.0497)	(0.2245)	(3.1802)	(0.0996)
lnOPEN	0.0362***	0.0245*	0.0268***	0.0243*	0.0324***	0.0268**	0.0318***	0.0239*	0.0339***	0.0302**
	(8.8382)	(1.7753)	(6.9984)	(1.7528)	(8.3805)	(2.0736)	(7.6125)	(1.7992)	(8.4639)	(2.1520)
lnFUND	-0.1558***	0.0653	-0.1386***	0.0272	-0.1620***	0.0465	-0.1586***	0.0561	-0.1497***	0.0184
	(-12.2187)	(1.4650)	(-11.6672)	(0.6219)	(-12.8994)	(1.1251)	(-12.6924)	(1.2990)	(-11.6783)	(0.4270)
$lnLQagcoo^2$	0.2480**	-0.0620	-0.0624	-0.0960	-0.0352	-0.1706	-0.0450	-0.1235	-0.0990*	-0.0907
	(2.5769)	(-0.3987)	(-1.4970)	(-0.5900)	(-0.8820)	(-1.1925)	(-1.0812)	(-0.7679)	(-1.9432)	(-0.5409)
λ	0.4545***		0.4720***		0.4270***		0.4390***		0.4419***	
	(9.4355)		(10.0767)		(8.6223)		(8.9979)		(9.1214)	
R^2	0.6755		0.6639		0.6341		0.6316		0.6414	
log-likelihood	570.4599		557.3725		532.1971		529.2804		537.9437	
Moran's I	0.2199		0.2415		0.2194		0.2146		0.2516	

Note: The t value is in parentheses. "***", "**", "*" indicate that they passed the test at the significant levels of 1%, 5%, and 10%, respectively.

4.3 Robustness Tests

To further corroborate the robustness of empirical results, the geographical weight matrix instead of the time weight matrix is used to test the spatial Durbin model, in which the geographical distance between cities is based on the spherical distance measured by longitude and latitude coordinates. As Table 8 shows, despite the differences of influence coefficients, the magnitude and significance of the coefficients of independent variable, moderating variable and interaction terms of independent variable and moderating variables are similar to the prior regression results, indicating that the empirical results of this study are robust and reliable.

5 Conclusions and Recommendations

With the increasing downward pressure on China's economy and the tightening of resources and environmental constraints, how to achieve a win-win situation between the promotion of industrial value chain and the construction of ecological environment has become a focal point concerned by the government and academia. Based on the change of population structure, this study takes it as the moderating variable to construct a mechanism of the effect of industrial collaborative agglomeration on environmental efficiency, in which the population structure is further subdivided into population distribution structure, population age structure, population spatial structure and population cultural structure, and measured by population density, aging, urbanization and quality. Meanwhile, this study uses the panel data of 66 cities at prefecture level in eastern China during 2009-2018, considering the impact of spatial correlation and the development of high-speed rail on the regional spatial pattern, and finally construct the spatial econometric model with time distance as the spatial weight matrix inorder to carry out the empirical test. This study draws the conclusions as below:

(1) spatial spillover effects of the environmental efficiency and industrial collaborative agglomeration have a positive significant effect on both of the local and neighboring regions, indicating the integration of industrial layout and the compactness of cross-regional flow of environmental factor pollution (Su et al., 2020). With respect to moderating effect, population density, population aging and population quality all produce positive and significant moderating impact on the relation between industrial collaborative agglomeration and environmental efficiency, indicating that these population elements are essential factors in promoting environmental efficiency by strengthening the promotion effect of industrial collaborative agglomeration. Population urbanization has not met the expectation in China, which shows that it is far from coordinating the construction of the ecological environment and industrial agglomeration, and there is also a “quality gap”, and even worse, immigrants from other cities cannot have the equal public services.

(2) the degree of opening to the outside world and environmental regulation improve environmental efficiency at least at 5% significant level, indicating environmental regulation plays a positive role in the green transformation and upgrading of industrial structure and improving the efficiency of clean energy. So the urban environmental efficiency is improved continuously, which supports Porter hypothesis. Moreover, infrastructure level and the proportion of tertiary industry increase worsen environmental efficiency at 1% significant level, while the positive effect of government intervention is not significant. It is reasonable to have the result that are not conducive to short-term environmental efficiency if there’s a big investment in short time and stagnancy and long-term effect of volatilization (Kuangg and Peng, 2012). Additionally, the excessive proportion of the tertiary industry restricts the improvement of environmental efficiency. For example, the transportation industry will lead to air pollution, and the

development of real estate may over-exploit ecological resources and occupy green space. It further proves the importance of accelerating the formation of a collaborative complex of advanced manufacturing and producer services to improve environmental efficiency.

The conclusions in this study provide several policy implications for better environmental efficiency.

(1) The coordinated governance system of regional ecological environment should be optimized. The results of Moran test and scatter chart reveal that there is a strong spatial correlation of environmental efficiency, indicating that the environment, as a cross-regional public goods, has obvious external effects. Therefore, all regions should reduce their dependence on heavy polluting industries, and strengthen cooperation with other regions in environmental control. The "low-by-low competition" model in the choice between economic output and environmental pollution should be strictly abandoned. Moreover, it is essential to form an environmental governance system of joint governance among the government, enterprises and the public. based on innovating the means of environmental regulation of government departments, improving the allocation mechanism of the rights and responsibilities of enterprises and the price formation mechanism of resources and environment, should be established as soon as possible to expand the scope of joint prevention and control regions.

(2) The construction of industrial collaborative agglomeration should be effectively accelerated. It is necessary to rationally lay out the construction of infrastructure such as informatization and transportation around the innovation of the chains of global value and industrial value. In promoting the construction of green production mechanism, all regions should follow the market-oriented evolution law of multi-level coordination of industrial collaborative agglomeration and explore a new communication mode that is more in line with the path of inter-industry spillover. Moreover, government encourages companies to apply clean technology, in order to accelerate the dissemination of knowledge and the sharing of green technology innovation results, and other regions to create a conducive environment for promoting the coordinated development mechanism of industries guided by advanced manufacturing and supported by modern producer services. Subsequently, the sustainable development of the industry and the optimization of environmental efficiency can be achieved by promoting the green whole industry chain.

(3) Internalize the power of population advantage into a booster for industrial green technology upgrading and eco-economic construction. It is important to promote the construction of new-type of people-oriented urbanization and improve the matching of public services for the equalization of the floating population. Additionally, urban population size should play its role on the transformation and upgrading of urban industries, based on urban spatial pattern and the capacity of ecological environment. At present, China faces the serious aging, while the consumption concept and travel mode of low-carbon environmental protection of the elderly have a positive effect on carbon emission reduction, which will optimize environmental efficiency. Appropriate policies can be formulated to guide the society to form a moderate and green consumption atmosphere, such as establishing a perfect old-age security system and encouraging low-carbon transformation of production and consumption patterns of young and middle-aged groups. Besides, by promoting the sustainable development of industry and ecology with population structure, the advantages of scientific and educational resources can be transformed into the advantages of talents, and implement the policy of introducing talents to accelerate the training of necessary technical talents through the linkage between schools and enterprises.

In this study, there is still much room for improvement in the empirical test. For example, the

indicators selected to measure environmental efficiency are not comprehensive enough, which can lead to differences between the research results and the reality. In addition, we can refine the empirical data to the enterprise level of manufacturing and productive service industries, and then explore the relationship between industrial collaborative agglomeration and environmental efficiency from a micro perspective, as well as the moderating effect of population structure on the relationship between them.

Ethical Approval

This work does not require any ethical approval.

Consent to Participate

The authors obtained consent from the responsible authorities at the institute/organization where the work has been carried out.

Consent to Publish

All authors agree with the content and give explicit consent to submit and publish.

Authors Contributions

Yue Zhu: Methodology, Software, Writing—Original draft preparation. Wenbo Du: Data curation, Validation, Visualization. Juntao Zhang: Writing—Review and Editing, Supervision. All authors have read and agreed to the published version of the manuscript.

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Competing Interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Availability of data and materials

Data and materials will be available from the corresponding author on reasonable request.

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Figures

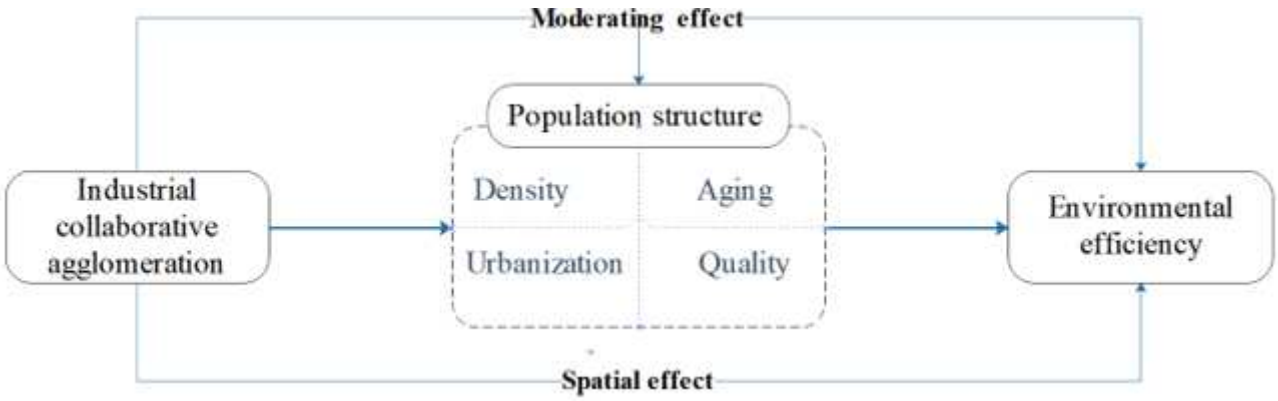

Figure 1

Conceptual framework of this study

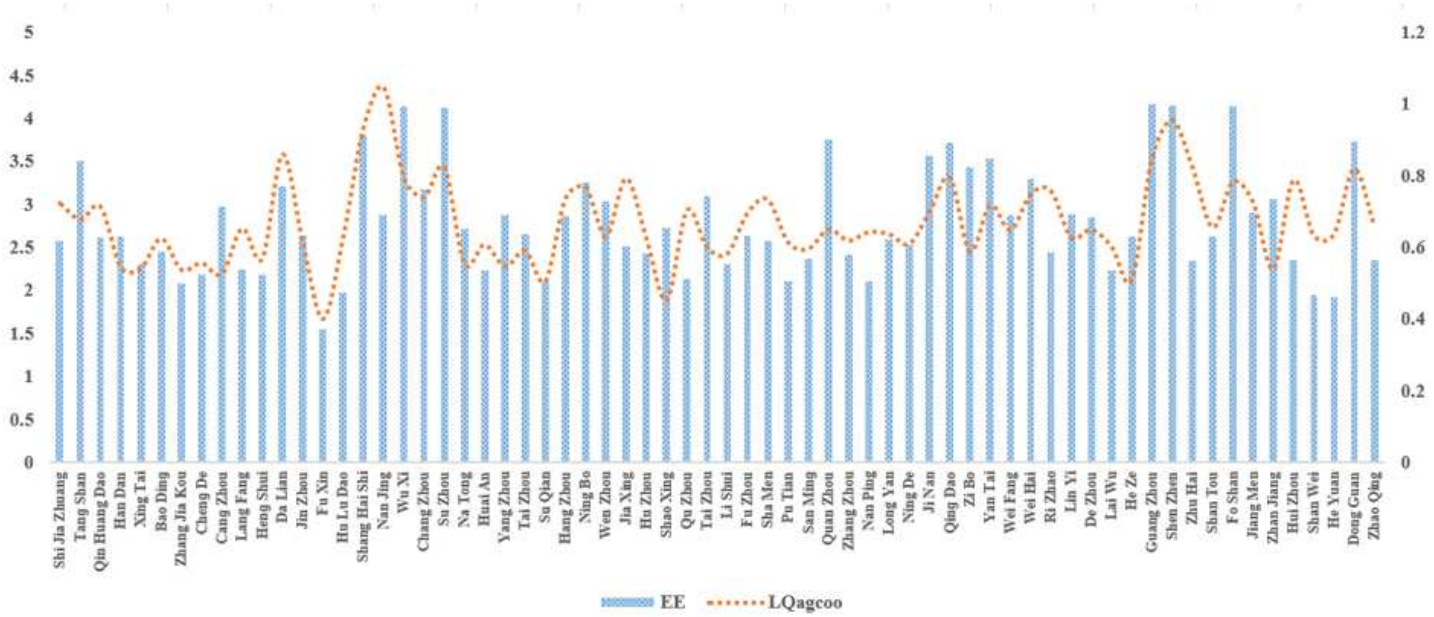

Figure 2

The average value of industrial collaborative agglomeration and environmental efficiency during 2009-2018

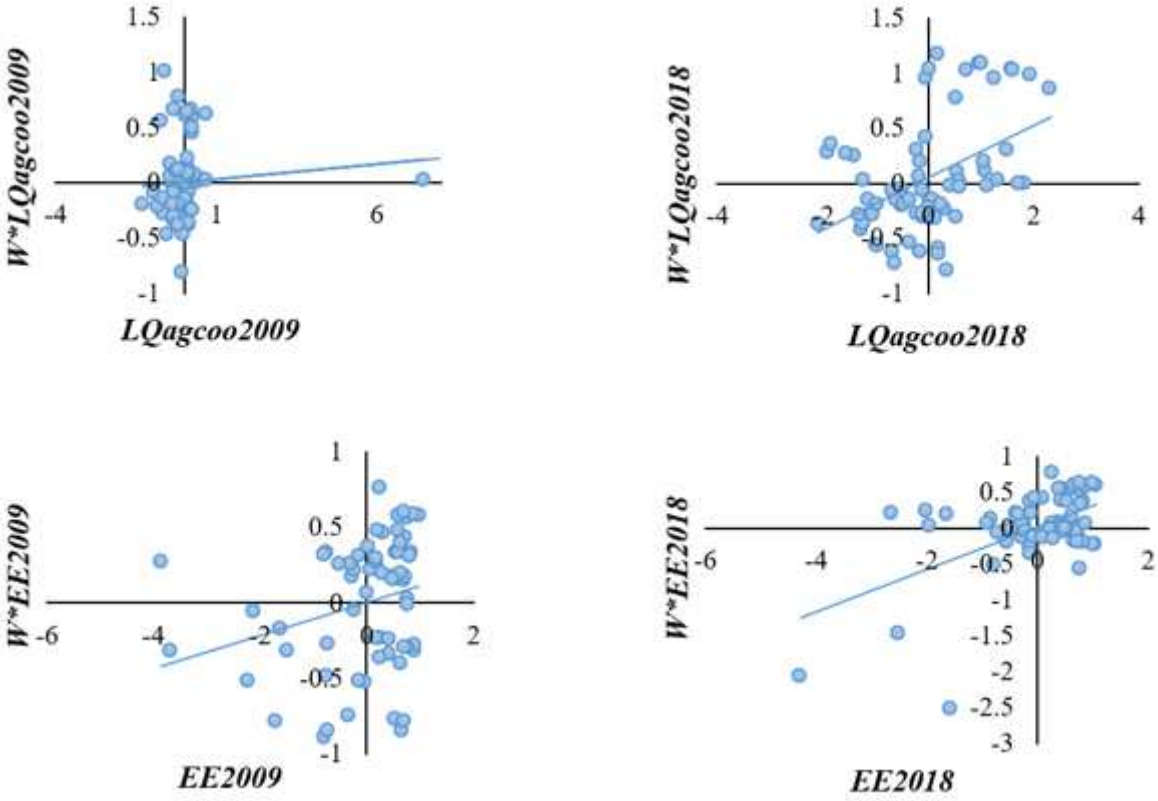

Figure 3

The Moran scatter plot of industrial collaborative agglomeration and environmental efficiency