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On industrial agglomeration and industrial carbon productivity --- impact mechanism and nonlinear relationship

Xiaoqian Zhang [a], Shujie Yao [a,b,*], Weiwei Zheng [c], Jing Fang [d]

[a] School of Economics and Business Administration, Chongqing University, Chongqing 400044, China
[b] Lianmin Institute of Economic Research, Liaoning University, Liaoning 111000, China
[c] Antai College of Economics and Management, Shanghai Jiao Tong University, Shanghai 200030, China
[d] School of Economics, Hangzhou Normal University, Hangzhou, Zhejiang 310000, China

A R T I C L E I N F O

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A B S T R A C T

This study focuses on examining the mechanisms of industrial agglomeration on industrial carbon productivity. A balanced panel dataset of 281 cities in China is used, covering the period from 2004 to 2020, to assess the combined economic and environmental effects of industrial agglomeration. The main research findings are: (1) Industrial agglomeration significantly raises industrial carbon productivity; (2) Industrial agglomeration indirectly increases industrial carbon productivity through technological progress and labor mismatch reduction; (3) Environmental regulations have a negative moderating role in the correlation between industrial agglomeration and industrial carbon productivity; (4) The relationship between industrial agglomeration and industrial carbon productivity is non-linear. One of the possible reasons for the non-linear relationship between industrial agglomeration and industrial carbon productivity is that the level of industrial agglomeration is too high and its effect on promoting technological progress is not significant. The innovation of this paper is that it focuses on the industrial sector, quantifies the learning and matching effects of industrial agglomeration, empirically analyzes how industrial agglomeration affects industrial carbon productivity, and explores the reasons for the nonlinear relationship between industrial agglomeration and industrial carbon productivity. These findings are valuable in guiding the industrial sector on improving industrial carbon productivity through agglomeration effects.

1. Introduction

Industrial carbon emissions are one of the major contributors to global climate change. According to statistics from the International Energy Agency, the industrial and building sectors account for over 40% of total global carbon emissions. This proportion is still increasing, especially in developing and emerging market countries.

Fig. 1 depicts the total industrial carbon emissions in China and their proportionate share of the overall national emissions in recent years. It is evident that China's industrial carbon emissions have steadily increased between 2004 and 2020, representing over 60% of the country's total emissions. This highlights the need for emission reductions in the industrial sector. However, it should be noted that the industrial sector plays a vital role in the national economy, contributing 39.9% to China's GDP in the most recent available data (National Bureau of Statistics of China). It is clearly unrealistic to excessively suppress the industrial sector in the pursuit of "dual carbon" (carbon peak and carbon neutrality), as it would significantly harm the country's economy. The reasonable solution is to reduce carbon emissions by raising industrial carbon productivity (hereafter, ICP) without significantly reducing the contribution of industrial production to the national economy.

The effect of industrial agglomeration on productivity theoretically encompasses two counteractive outcomes. On one hand, when firms form clusters, they can share technology and information, utilize resources efficiently, and reduce production costs, resulting in higher productivity [1,2]. On the other hand, crowding effects from over-agglomeration may lead to lower productivity [3]. Due to the complex effect of industrial agglomeration on productivity, the relationship has attracted serious attention from researchers and policymakers. According to the existing literature, the impacts of industrial agglomeration on productivity vary and can be categorized as positive, negative, or non-linear, as summarized in Table 1.

According to Table 1, we can see that when defining productivity, the vast majority of scholars assess carbon productivity [7,8] or green

* Corresponding author. Lianmin Institute of Economic Research, Liaoning University, Liaoning 111000, China.
E-mail address: yaoshujie@cqu.edu.cn (S. Yao).

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productivity [5,16] from a sector-wide perspective or focus on the energy efficiency [18,19] of a particular sector. It is important to point out that the productivity measured from a sector-wide perspective is not precise to a particular sector, and it has been pointed out that industrial agglomeration occurs mainly in urban areas, making it difficult for the exchange and cooperation of industrial enterprises within cities to influence carbon emissions from agriculture, forestry, animal husbandry, and fishing [20]. However, the share of carbon emissions from the agricultural sector in China is as high as 16–17%, and the total amount has been growing. More importantly, carbon productivity levels are not the same among different industries, and their trends are not synchronized, so if they are confused, their research conclusions may not be representative. In addition, the energy efficiency of a sector is not equivalent to its carbon productivity. When energy efficiency is the same, carbon productivity may also vary if the energy structure of the two sectors is different. In brief, the extant literature has not paid serious attention to ICP when discussing the impact of industrial agglomeration on productivity. Similarly, the analysis of factors affecting ICP has only focused on energy structure [21,22], FDI [23], technological progress [24,25], demographic factors [26], and environmental regulation [27], among other variables. In other words, few researches have concentrated on the effect of industrial agglomeration on ICP.

Second, Table 1 shows that most extant studies only concentrate on the direct impact of industrial agglomeration on productivity [4,6]. Although the mediating role of technological progress has also been discussed, how industrial agglomeration affects ICP has not been well studied. Based on the external theory of agglomeration, agglomeration contains three different effects: learning, matching, and sharing [28]. Although the sharing effect is not easily defined, the learning effect can be measured by technological progress, while the matching effect can be assessed by whether resources are efficiently allocated. Based on the theory of comparative advantage in trade, polluting manufacturers will choose to move to regions with fewer environmental regulations to attain more production gains with less environmental responsibility, which is implied by the so-called pollution paradigm theory. This implies that environmental regulation also influences the correlation between industrial agglomeration and ICP.

Finally, according to Table 1, we find that more scholars' research results have demonstrated the non-linear relationship between agglomeration and productivity [12,14]. Unfortunately, scholars only focus on the difference in magnitude or direction of the effect of industrial agglomeration on productivity at the left and right sides of the threshold, while the reasons behind this phenomenon have not been well explained.

In summary, the existing literature is concentrated on the effect of industrial agglomeration on sector-wide carbon productivity, green productivity, or sector-specific energy efficiency and does not focus on ICP. How industrial agglomeration affects ICP has not been demonstrated, and the reasons behind the non-linear relationship between industrial agglomeration and ICP have not been well explained.

This paper will make the following contributions: (1) It innovatively explores the effect of industrial agglomeration on ICP and fills a literature gap in this important contemporary issue in Chinese cities; (2) The mechanism of industrial agglomeration on ICP is elaborated with technological progress and resource mismatch as mediating variables and environmental regulation as moderating variables; (3) To examine the non-linear relationship between industrial agglomeration and ICP and to analyze the reasons for it.

The rest of the paper is structured as follows. The second section displays the theoretical framework and research hypotheses. The third section defines the model, variables, and data. The empirical results are explored in the fourth section. The fifth section presents the mechanism analysis. The last section concludes with policy recommendations.

2. Theoretical mechanisms and research hypotheses

2.1. The total effect of industrial agglomeration on ICP

According to the expansion of existing literature, the impact of industrial agglomeration on ICP has two sides. Industrial agglomeration can enhance ICP. Industrial agglomeration can stimulate the sharing and recycling of industrial resources, and reduce duplication of production and waste by achieving efficient synergy in industrial chains, thus improving ICP [29,30]. Additionally, industrial agglomeration can reduce ICP. Firstly, the competitive pressure among firms will increase after industrial agglomeration, and in order to reduce costs and improve competitiveness, firms may tend to adopt high carbon emission production methods [31]. Secondly, over-agglomeration may produce congestion effects, leading to resource misallocation that is ultimately detrimental to ICP [32,33]. Obviously, the direction of the impact of industrial agglomeration on ICP depends on the combined result of these two forces. Based on these points, we propose Hypotheses 1a and 1 b.

Hypothesis 1a. Industrial agglomeration can increase ICP.

Hypothesis 1b. Industrial agglomeration can decrease ICP.

2.2. The mediating mechanism of technological progress

The learning effect of agglomeration can lead to technological progress and thus increase productivity [34,35]. Specifically, industrial

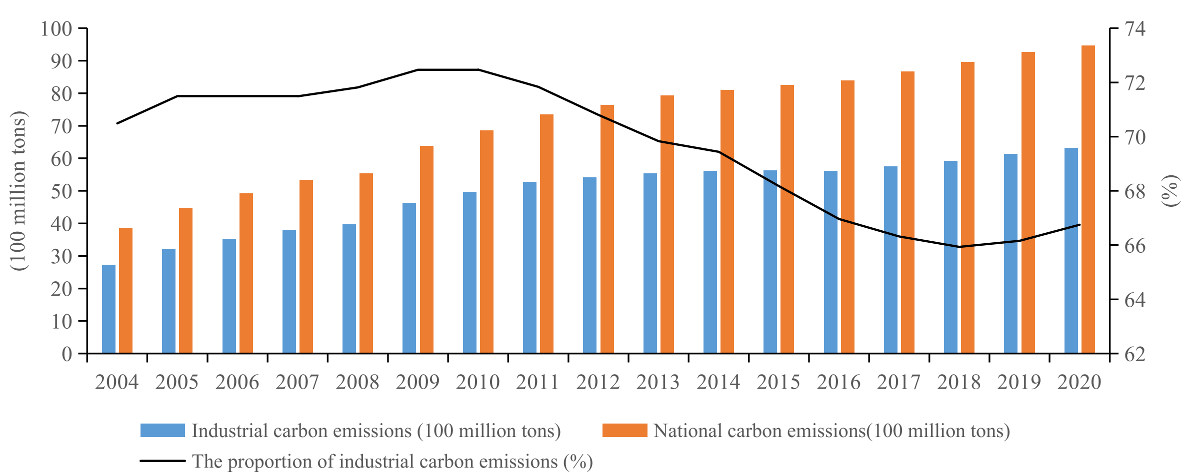

Fig. 1. Industrial carbon emissions and the national shares in China, 2004–2020.
Sources: Calculated from *China Energy Statistical Yearbook*

agglomeration can form an industrial chain, making the cooperation between enterprises closer and more efficient, thus promoting technological cooperation and innovation among peers and accelerating the technological upgrading of the whole industry [36,37]. Moreover, industrial agglomeration enables enterprises to form complementary advantages in logistics and procurement to improve the efficiency of the supply chain. In this way, raw materials and technical support can be more easily obtained in production through research and development, thus accelerating technological upgrading and improving firm performance [38]. In addition, technological progress can effectively promote cleaner production and end-treatment, thus playing an important role in improving ICP [39]. As a result, we put forward Hypothesis 2.

Hypothesis 2. Technological progress plays a positive mediating role in the impact of industrial agglomeration on ICP.

2.3. The mediating mechanism of resource allocation

Based on the new economic geography theory pioneered by Ref. [40]; industrial agglomeration has a significant effect on resource allocation. Under the market structure of increasing returns to scale and monopolistic competition, industrial agglomerations form regional agglomerations of related industries through the cumulative effect of backward and forward linkages. The agglomeration effect influences the allocation of capital and labor within the agglomeration area [41,42]. Regarding the optimal allocation of capital, because the industrial chain in the agglomeration area is more reasonable and complete, the flow of capital here will be smoother, thus playing the role of optimal allocation of capital. Regarding the allocation of labor, Marshall puts forward the "labor market reservoir" of industrial agglomeration in his book "Principles of Economics" [43]. Subsequently, some scholars have also demonstrated empirically that industrial agglomeration can optimize labor allocation [44,45]. The optimal allocation of resources can improve productivity [46]. Therefore, we propose Hypothesis 3a and3b.

Hypothesis 3a. Industrial agglomeration can increase ICP by reducing capital mismatches.

Hypothesis 3b. Industrial agglomeration can increase ICP by reducing labor mismatches.

2.4. The moderating effect of environmental regulation

On the one hand, environmental regulation has an innovation compensation effect. Appropriate environmental regulation may stimulate technological innovation, change the mode and layout of industrial production, and improve ICP [47]. To be specific, to offset the cost of environmental regulation, industrial enterprises in the agglomeration area will seek more environmentally friendly production modes, reduce excessive use of fossil fuels including coal, oil, and gas, and improve environmental quality [48]. On the other hand, environmental regulations may increase the production difficulty of industrial operators within the agglomeration area, and thus reduce the attraction to industrial operators outside the agglomeration area, resulting in stagnation or decline in the scale and quantity of the agglomeration [49]. Agglomeration's economic effect cannot be brought into play, which harms ICP. Therefore, we propose hypotheses 4a and 4 b.

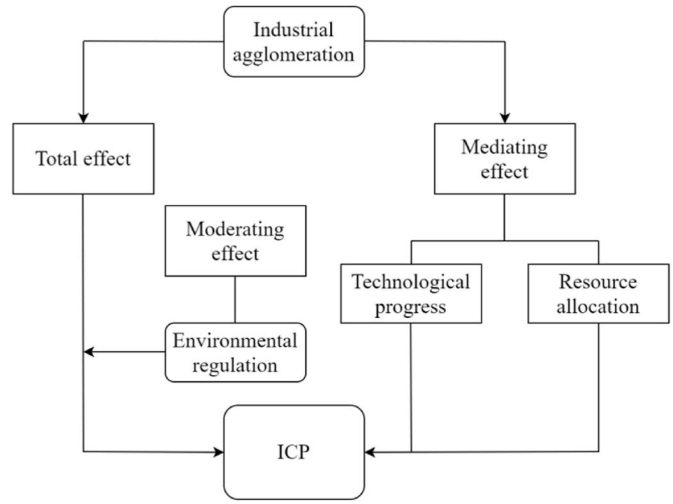

Fig. 2. The impact mechanism between industrial agglomeration and ICP.

Hypothesis 4a. Environmental regulation makes a positive moderating role in industrial agglomeration and ICP.

Hypothesis 4b. Environmental regulation makes a negative moderating role in industrial agglomeration and ICP.

According to the above discussion of theoretical mechanisms, we plotted a mechanism diagram (Fig. 2) of the correlation between industrial agglomeration and ICP.

3. Models, variables and data

3.1. Benchmark model

An individual time double fixed effects model is constructed based on Hypothesis 1 to investigate the impact of industrial agglomeration on

Table 1
Summary of empirical findings of industrial agglomeration on productivity.

References	Period	Sample	Explained variable	Mediating variable	Results	Including ICP (Yes/No)
[4]	1994–1995	Industries firm of India	Productivity in Indian industry	No	Positive	No
[5]	2005–2018	284 cities in China	Green total-factor productivity	Technical progress	Positive	No
[6]	1986–2015	Iran's Food firm	Productivity in Iran's Food sector	No	Positive	No
[7]	2000–2018	Chinese provinces	Carbon productivity	No	Positive	No
[8]	2006–2017	Chinese provinces	Carbon productivity	No	Positive	No
[9]	2003–2017	281 cities in China	Carbon productivity	Technical progress	Positive	No
[10]	2005–2017	35 economies in Africa	Carbon productivity	No	Negative	No
[11]	2000–2011	Chinese provinces	Tourism labor productivity	No	Negative	No
[12]	1998–2017	Chinese provinces	Carbon productivity	Technical progress	Nonlinear	No
[13]	2000–2005	Chinese firm	Firm-level productivity	No	Nonlinear	No
[14]	2009–2017	21 economies in Africa	Energy productivity	No	Nonlinear	No
[15]	1991–2019	Chinese provinces	Agricultural carbon productivity	Technical progress	Nonlinear	No
[16]	2003–2018	281 cities in China	Green total-factor productivity	No	Nonlinear	No
[17]	2004–2018	Yangtze River Economic Belt's	Carbon productivity	Technical progress	Nonlinear	No
[18]	1995–2013	Chinese provinces	Energy efficiency in textile industry	No	Nonlinear	No
[19]	1990–2013	Chinese provinces	Energy efficiency in paper industry	No	Nonlinear	No

Note: A nonlinear relationship refers to a situation where the relationship between two or more variables does not follow a linear pattern, meaning it cannot be accurately described using a straight line. In a nonlinear relationship, as one variable changes, the other variable does not change at a constant rate.

ICP. With the aim of eliminating the effect of heteroskedasticity, all variables are treated logarithmically, and the specific model is shown in equation (1) [50]:

$$\ln icp_{it} = \alpha_0 + \alpha_1 \ln agg_{it} + \sum_{k=2}^{6} \alpha_k X_{it} + u_i + v_t + \varepsilon_{it} \tag{1}$$

In equation (1), *icp* is industrial carbon productivity, *agg* is industrial agglomeration, *X* refers to a set of control variables (see Section 3.3 for details), *i* and *t* suggest city and year, respectively, α_0 refers to the constant term, α_1 and α_k denote the regression coefficients of industrial agglomeration and control variables, respectively, u_i refers to the city fixed effect, v_t refers to the time fixed effect, and ε refers to the random disturbance term.

To investigate the mediating role of technological advancement and resource allocation, the following model for mediating effect is created by consulting the procedure of [51]:

$$\ln M_{it} = \gamma_0 + \gamma_1 \ln agg_{it} + \sum_{k=2}^{6} \gamma_k X_{it} + u_i + v_t + \varepsilon_{it} \tag{2}$$

$$\ln icp_{it} = \beta_0 + \beta_1 \ln agg_{it} + \beta_2 \ln M_{it} + \sum_{k=3}^{7} \beta_k X_{it} + u_i + v_t + \varepsilon_{it} \tag{3}$$

In the above equations, M_{it} represents the mediating variable, here refers to technological progress (*t*) and resource mismatch (*mis*); γ_0 and β_0 are constant terms; the remaining γ and β are regression coefficients of related variables. In equation (2), γ_1 represents the effect of the explanatory variable on the mediating variable. In equation (3), β_1 is the regression coefficient of the explanatory variable to the explained variable after controlling the mediating variable and the control variable; β_2 stands for the effect of the mediating variable on the explained variable. If γ_1 in equation (2) and β_2 in equation (3) are both significant, then the mediating effect of the mediating variable is established. At the same time, based on hypothesis 4, we construct the following moderating effect model [52]:

$$\ln icp_{it} = \theta_0 + \theta_1 \ln agg_{it} + \theta_2 \ln er_{it} + \theta_3 \ln agg_{it} \times \ln er_{it} + \sum_{k=4}^{7} \theta_k X_{it} + u_i + v_t + \varepsilon_{it} \tag{4}$$

In the above formula, θ_0 represents the constant term, the other θ's are the regression coefficients of related variables; ln*er* stands for moderating variable environmental regulation. If the regression coefficients θ_1 and θ_3 in equation (4) are significant, it suggests that environmental regulation makes a moderating effect on the relationship between industrial agglomeration and ICP.

3.2. Variable settings and data sources

3.2.1. Explained variable: industrial carbon productivity

We measure ICP using the SBM model. The specific calculation steps are presented as follows. First, we calculate the industrial carbon emissions of each city in the sample years. Currently, statistics on urban industrial energy mainly include natural gas, liquefied petroleum gas, and electricity. The specific calculation formula for industrial carbon emissions is shown in equation (5) [53].

$$I = C_n + C_p + C_e = uE_n + vE_p + \alpha \times (wE_e) \tag{5}$$

Where C_n, C_p and C_e respectively represent the carbon emissions from industrial natural gas, industrial liquefied petroleum gas and industrial electricity; E_n, E_p and E_e respectively represent the consumption of industrial natural gas, industrial liquefied petroleum gas and industrial electricity; *u* and *v* represent the carbon emission coefficients of industrial natural gas and industrial liquefied petroleum gas, α is the greenhouse gas emission coefficient of coal-electric fuel chain, *w* is the proportion of coal power generation in total power generation. Secondly, industrial fixed asset investment, industrial employees and industrial electricity consumption are used as input variables; gross industrial output as expected output; industrial carbon emissions as undesirable outputs. Thirdly, The ML index was calculated using MaxDEA software. Finally, the ML index was transformed into total factor ICP with reference to the [54]. Assuming a base year of 2004 TF P = 1, the 2005 TF P is equal to the 2004 TF P multiplied by the 2005 ML index and so on.

Industrial agglomeration (*agg*). According to Ref. [55]; and [56]; the location entropy method is adopted for measuring the level of industrial agglomeration in each city with the following formula:

$$agg_{it} = \frac{EMI_{it}/EM_{it}}{\sum EMI_{it}/\sum EM_{it}} \tag{6}$$

In equation (6), EMI_{it} refers to the industrial employees in the city *i* and year *t*. EM_{it} is the number of employees in city *i* and year *t*. Since the data on the number of industrial sector employees are not directly available, this paper uses the difference between the number of employees in the secondary industry (manufacturing and construction) and the number of employees in the construction industry to estimate them.

3.2.2. Mediating and moderating variables

(1) Technological progress (*t*). Hypothesis 2 proposes that technological progress is a mediating variable for industrial agglomeration to affect ICP. Previous studies have mostly used the number of patent registrations over the years in measuring technological progress [57,58], and considering that the study in this paper concentrates on the industrial sector, we aggregate the number of green patents granted for all industrial enterprises at the city level over the years to indicate technological progress.

(2) Resource mismatch (*mis*). Hypothesis 3 proposes that resource allocation is a mediating variable for industrial agglomeration to affect ICP. Resource allocation includes capital allocation and labor allocation. The more efficient the resource allocation, the lower the resource mismatch index. Referring to the method of [59]; the industrial capital mismatch index (*kmis*) and labor mismatch index (*lmis*) are calculated for each city as presented in equations (7) and (8).

$$kmis_i = \frac{1}{\gamma_{ki}} - 1 \tag{7}$$

$$lmis_i = \frac{1}{\gamma_{li}} - 1 \tag{8}$$

Where γ_{ki} and γ_{li} denote the capital and labor price distortion coefficients, respectively, as defined in equations (9) and (10).

$$\gamma_{ki} = \left(\frac{k_i}{k}\right) \Big/ \left(\frac{s_i \beta_{ki}}{\beta_k}\right) \tag{9}$$

$$\gamma_{li} = \left(\frac{l_i}{l}\right) \Big/ \left(\frac{s_i \beta_{li}}{\beta_l}\right) \tag{10}$$

Where k_i/k denotes the ratio of industrial capital used in city i over total national industrial capital, s_i denotes the share of industrial output in city *i* over total national industrial output, $s_i\beta_{ki}/\beta_k$ is the ratio of capital used in region *i* when capital is efficiently allocated, and γ_{ki} reflects the degree of mismatch of capital. L_i/l denotes the ratio of labor to total labor in city *i*, $s_i\beta_{li}/\beta_l$ is the proportion of labor used in region *i* when labor is efficiently allocated. γ_{li} reflects the degree of labor mismatch. Total output is denoted as the total industrial output in each city. Labor input is expressed as the number of people employed in the industrial sector in each city. Industrial capital input is calculated with the perpetual inventory method.

(3) Environmental regulation (*er*). Hypothesis 4 proposes that environmental regulation makes a regulating impact on the relationship between industrial agglomeration and ICP. Referring to Ref. [60]; environmental regulation is represented by the pollution control level of pollutants. However, a single pollutant control level may be subjective and one-sided. Therefore, the entropy method is adopted for objectively calculating the environmental regulation intensity of each city by selecting three single indexes: the comprehensive utilization rate of general industrial solid waste, the centralized treatment rate of the sewage treatment plants as well as the harmless treatment rate of household waste. The entropy method is formulated as follows [61].

The first step is the standardization of the indicator, and the standardization formula for the positive indicator is:

$$X_{ij}^{'} = \frac{X_{ij} - \min(X_j)}{\max(X_j) - \min(X_j)} \tag{11}$$

The standardization of the reverse indicator is:

$$X_{ij}^{'} = \frac{\max(X_j) - X_{ij}}{\max(X_j) - \min(X_j)} \tag{12}$$

Where X_{ij} denotes the value of the jth indicator in the ith year.

In the second step, the share of each indicator in the sum of the indicators is calculated for each year P_{ij}:

$$P_{ij} = \frac{X_{ij}^{'}}{\sum_{i=1}^{m} X_{ij}^{'}} \tag{13}$$

In the third step, the entropy value of the indicator e_j is calculated:

$$e_j = \frac{-1}{\ln m} \sum_{i=1}^{m} P_{ij} \ln P_{ij} \tag{14}$$

In the fourth step, the coefficient of variation g_j of the indicator is calculated:

$$g_j = 1 - e_j \tag{15}$$

In the fifth step, the entropy weights w_j of the evaluation indicators are calculated:

$$w_j = \frac{g_j}{\sum_{j=1}^{n} g_j} \tag{16}$$

In the sixth step, the normalized data is multiplied with the weights to obtain a composite score:

$$Z_j = \sum_{i=1}^{n} w_j \times X_{ij}^{'} \tag{17}$$

3.2.3. Control variables

(1) Population size (*p*). This variable is expressed by the total population of the city. Although the expansion of population size will stimulate the convergence of innovative factors and intensive utilization of resources to a certain extent, thus improving urban efficiency, it will also promote industrial activities due to the increase of energy consumption and the expansion of consumer demand, thus generating downward pressure on urban ecological environment.

(2) Science and education input (*r*). This variable is expressed using the government expenditure on science and education as a percentage of total fiscal expenditure [39]. The improvement in science and technology innovation is an important support for industry to realize green transformation and low carbon development, which helps to enhance the level and efficiency of industrial scientific and technological progress, controls pollutant emissions and improves ICP [62].

(3) Environmental regulation (*er*). The calculation of environmental regulation is the same as above. On the one hand, environmental regulation can urge companies to save energy and reduce emissions, and prompt them to choose cleaner production methods to improve ICP. On the other hand, harsh environmental regulation may lead to higher production costs for industrial enterprises resulting in lower profits, thus reducing ICP.

(4) Energy structure (*es*). The energy mix is expressed using the share of coal in the total energy consumption [63]. A coal-based energy mix generally reduces ICP [64].

(5) Foreign direct investment (*fdi*). This is expressed as a percentage of GDP using FDI [52]. According to the hypothesis of “pollution paradigm”, the intercountry free trade offers conditions for shifting the pollution-intensive industries to those nations with low pro-environmental intensity. Foreign direct investment may reduce ICP.

The sources of relevant data include the *China Energy Statistical Yearbook*, CNRDS database, *China City Statistical Yearbook*, as well as statistical yearbooks of the entire investigated cities in the sampling years. To sustain consistency, the constant prices in 2004 are used to compute the values of the entire economic parameters, and their natural logarithms are taken. Table 2 details the fundamental statistics for the parameters.

4. Empirical results and analysis

4.1. Results of baseline regression

In Table 3, the industrial agglomeration’s influence over ICP is detailed under time and individual fixed effects. Based on the regression results, the coefficient for industrial agglomeration’s influence over ICP is positive, which passes the 1% significance test in the case of progressive incorporation of control variables, suggesting the comparative robustness of the results. Upon incorporation of the entire control variables, the ICP rises by 0.021% for every 1% elevation in the level of industrial agglomeration. This empirical result supports hypothesis 1a and rejects hypothesis 1b. The possible reason is that although the influence of industrial agglomeration on ICP has two sides, its negative externalities mainly come from the later stage of industrial agglomeration, and most cities in China are still in the primary stage of industrial agglomeration, so industrial agglomeration has a significant effect on ICP during the study period.

Regarding control variables, population size makes a significantly positive impact on ICP, which may be due to the fact that the expansion of population size can promote the convergence of innovation factors and intensive use of resources, which enhances ICP. The coefficient of the effect of R&D investment on ICP is significantly negative, possibly

Table 2
Descriptive statistics of the variables.

Variables	Obs.	Mean	Std. Dev.	Min	Max
ln*icp*	4777	0.054	0.094	−0.491	0.523
ln*agg*	4777	−0.138	0.454	−2.272	1.112
ln*t*	4777	1.819	1.734	0.000	7.105
ln*kmis*	4777	−1.397	1.131	−12.948	1.197
ln*lmis*	4777	−0.705	1.145	−7.970	1.890
ln*p*	4777	5.862	0.698	2.819	8.150
ln*r*	4777	2.939	0.266	−1.117	3.907
ln*er*	4777	−0.361	0.311	−2.750	−0.004
ln*es*	4777	4.187	0.375	0.573	5.169
ln*fdi*	4777	−0.040	1.410	−7.277	2.985

Table 3
Results of the effect of industrial agglomeration on ICP.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
ln*agg*	0.021***	0.019***	0.019***	0.019***	0.020***	0.021***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
ln*p*		0.101***	0.104***	0.104***	0.105***	0.105***
		(0.022)	(0.022)	(0.022)	(0.022)	(0.022)
ln*r*			−0.003	−0.003	−0.012	−0.013*
			(0.008)	(0.008)	(0.008)	(0.008)
ln*er*				0.012*	0.008	0.008
				(0.007)	(0.007)	(0.007)
ln*es*					−0.079***	−0.080***
					(0.010)	(0.010)
ln*fdi*						−0.003*
						(0.002)
constant	0.086***	−0.503***	−0.508***	−0.502***	−0.152	−0.143
	(0.005)	(0.125)	(0.126)	(0.126)	(0.133)	(0.133)
City fixed effect	yes	yes	yes	yes	yes	yes
Year fixed effect	yes	yes	yes	yes	yes	yes
R^2	0.260	0.263	0.263	0.264	0.273	0.274
Obs	4777	4777	4777	4777	4777	4777

Note: Standard errors in parentheses, *, **, and *** indicates statistical significance at 10%, 5%, and 1% levels, respectively.

because excessive R&D investment puts pressure on the cost of production. Another possibility is that R&D investment aimed at expanding production scale may effectively increase energy consumption and produce more carbon emissions, thus leading to lower ICP [65]. The coefficient of environmental regulation is not of significance. The coal-based energy mix also reduces ICP, which is consistent with our economic intuition. The significantly negative coefficient of foreign direct investment could be attributed to the fact that foreign investors have shifted high polluting and high emitting industrial enterprises to China, which adversely affects the carbon productivity of the local industrial sector [66,67].

4.2. Robustness tests

With the purpose of ensuring the robustness of the benchmark regression results, the present study mainly tests from the following perspectives. Firstly, core explanatory variables are replaced [68]. believe that employment density can also be adopted for measuring the degree of agglomeration, and industrial employment per unit area of a city is employed to represent the level of industrial agglomeration. The regression results are presented in column (1) of Table 4. The second method to test robustness is to replace the explained variable. Here, we use single-factor ICP instead of the total factor ICP in the above formula for testing. The regression results are shown in column (2) of Table 4. Third, the estimation method is changed, and column (3) of Table 4 reports the estimation results using the clustering robust OLS method. Finally, considering that municipalities directly under the central government and provincial capitals have higher administrative levels and policy advantages, and their industrial development levels are also relatively high, we exclude municipalities from the sample directly under the central government and provincial capitals for robustness testing. The corresponding test results are displayed in column (4) of Table 4. Based on the results, it can be found that our regression results are still robust after replacing the core explanatory variables, explained variable, changing the estimation method and estimating the sample.

Table 4
Robustness test results.

Variables	(1)	(2)	(3)	(4)
ln*agg*	0.037***	0.010***	0.021***	0.025***
	(0.004)	(0.003)	(0.008)	(0.007)
constant	−0.252*	0.535 (0.669)	−0.182	0.036 (0.144)
	(0.132)		(0.310)	
Control variable	yes	yes	yes	yes
City fixed effect	yes	yes	yes	yes
Year fixed effect	yes	yes	yes	yes
R^2	0.283	0.458	0.314	0.280
Obs	4777	4777	4777	4284

Note: Standard errors in parentheses, *, **, and *** indicates statistical significance at 10%, 5%, and 1% levels, respectively.

4.3. Endogeneity test

Considering that industrial agglomeration and ICP may promote each other, that is, regions with high ICP will also attract industrial enterprises to settle in, deepening the degree of industrial agglomeration. Therefore, it becomes necessary to deal with the potential endogeneity issue. Multiplying geographic slope by year was used as an instrumental variable [69]. In general, enterprises tend to build factories in flat areas, thus cities with flat terrain generally have a higher degree of industrial agglomeration. However, geographical slope does not directly affect ICP, so this variable meets the requirements of instrumental variable. Columns (1) and (2) of Table 5 present the findings of two-stage least squared (2 S LS) regression for

Table 5
Endogeneity test.

Variables	(1)ln*agg*	(2)ln*icp*	(3)ln*icp*
IV	−0.123***		
	(0.011)		
ln*agg*		0.055***	0.013*
		(0.019)	(0.007)
constant	0.987 (0.188)	−0.066*	0.086
		(0.035)	(0.132)
Kleibergen-Paap rk LM statistic	118.593***		
Kleibergen-Paap rk Wald F statistic	124.911		
Control variable	yes	yes	yes
City fixed effect	yes	yes	yes
Year fixed effect	yes	yes	yes
R^2	0.300	0.201	0.303
Obs	4777	4777	4496

Note: Standard errors in parentheses, *, **, and *** indicates statistical significance at 10%, 5%, and 1% levels, respectively.

instrumental variables. According to the results in column (1), we can see that Kleibergen-Paap rk LM passes the 1% significance test, indicating that there exists a correlation between instrumental variables and endogenous variables. Moreover, the test result of F statistic rejects the hypothesis of weak instrumental variables. Combined with the regression result of industrial agglomeration in column (2), it can be concluded that industrial agglomeration still makes a promoting impact on ICP. In addition, a one-stage lag was applied to all explanatory variables to mitigate the effect of the reverse causality problem, and this regression results are reported in column (3). Obviously, the estimated results of one-stage lag treatment for explanatory variables also support the research conclusion that industrial agglomeration can improve ICP.

5. Mechanism analysis

5.1. Test of mediating effect and moderating effect

Models (1), (3) and (5) in Table 6 represent the impact of industrial agglomeration on the intermediary variables, respectively. The results show that industrial agglomeration has a significant impact on technological progress and labor mismatch, but has no significant impact on capital mismatch. The findings of models (2), (4) and (6) display that the impact of technological progress (t) and labor mismatch ($lmis$) on ICP passes the 1% significance test, while the effect of capital mismatch on ICP fail to pass the significance test. According to the above regression results, industrial agglomeration can improve ICP by improving industrial technological progress. This empirical result supports hypothesis 2. Industrial agglomeration can improve ICP by reducing labor mismatch. Capital mismatch has no mediating effect. This empirical result supports hypothesis 3b and rejects hypothesis 3a.

Model (7) in Table 6 is the estimation result of the impact of industrial agglomeration on ICP after adding interactivity. The coefficient of ln*agg* is significantly positive, with the coefficient of ln*agg* × ln*er* being significantly negative, suggesting that environmental regulation makes a negative role in regulating the relationship between industrial agglomeration and ICP. The possible explanation is that in order to comply with emission standards, companies have to upgrade their equipment or use new materials, which increases unit costs, decreases demand, and ultimately reduces ICP. This empirical finding supports Hypothesis 4b, but not Hypothesis 4a.

5.2. Discussion of nonlinear relations

According to the life cycle theory of agglomeration, under the combined action of centripetal and centrifugal forces, industrial agglomeration may show obvious stage differences [70], and its specific forms include agglomeration, diffusion and equilibrium. This difference is likely to have a nonlinear impact on ICP. To test whether a nonlinear correlation exists between industrial agglomeration and ICP, the panel threshold model [71] is adopted for analysis. The model is constructed as follows:

$$\begin{aligned}\ln icp_{it} = \alpha + \beta_1 \ln agg_{it} + \beta_j \sum \ln control_{it} + \varphi_1 \ln agg_{it} \cdot I(q_{it} \le \lambda_1) + \varphi_2 \ln agg_{it} \cdot I(\lambda_1 < q_{it} \le \lambda_2) \\ + \ldots + \varphi_n \ln agg_{it} \cdot I(\lambda_{n-1} < q_{it} \le \lambda_n) + u_i + v_t + \varepsilon_{it}\end{aligned} \tag{18}$$

Where, q_{it} refers to the threshold variable, and the threshold variable here is industrial agglomeration (agg_{it}); λ_1, λ_2 … λ_n are a set of the threshold values; I (·) is the indicating function, which takes 1 if the condition in parentheses is met, and 0 if not; β and φ are regression coefficients of corresponding variables, and other variables are the same as in equation (1).

Before identifying the specific form of the model, we need to determine the number of thresholds. In accordance with the test results in Table 7, industrial agglomeration passes the single threshold test and rejects the double threshold hypothesis, with a threshold value of 0.191. Next, based on the threshold test results, this paper further estimated the nonlinear impact of industrial agglomeration on ICP.

According to the regression results in Table 8, with the industrial agglomeration level being at the left side of the threshold value, the effect of industrial agglomeration on ICP is 0.024 and significant at 1%. With the level of industrial agglomeration being at the right side of the threshold value, the impact of industrial agglomeration on ICP is 0.008, but it does not pass the significance test of 10%. The result suggests that industrial agglomeration can improve ICP only at appropriate levels. The possible reason is that factor resource crowding may occur in the later stage of industrial agglomeration, resulting in the imbalance of resource allocation, thus cancelling out the positive effects of agglomeration such as scale effect and technology spillover. In addition, in the

Table 6
Test results of mediating and moderating effects.

Variables	ln*t*	ln*icp*	ln*kmis*	ln*icp*	ln*lmis*	ln*icp*	ln*icp*
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ln*agg*	0.194*** (0.052)	0.019*** (0.007)	0.056 (0.059)	0.021*** (0.007)	−0.574*** (0.054)	0.019*** (0.007)	0.014* (0.008)
ln*t*		0.007*** (0.002)					
ln*kmis*				0.001 (0.002)			
ln*lmis*						−0.004** (0.002)	
ln*agg* × ln*er*							−0.019* (0.011)
constant	−5.593*** (1.065)	−0.104 (0.133)	−4.978*** (1.208)	−0.137 (0.133)	4.894*** (1.100)	−0.124 (0.133)	−0.147 (0.133)
Control variable	yes	yes	yes	yes	yes	yes	yes
City fixed effect	yes	yes	yes	yes	yes	yes	yes
Year fixed effect	yes	yes	yes	yes	yes	yes	yes
R^2	0.691	0.276	0.044	0.274	0.051	0.274	0.274
Obs	4777	4777	4777	4777	4777	4777	4777

Note: Standard errors in parentheses, *, **, and *** indicates statistical significance at 10%, 5%, and 1% levels, respectively.

Table 7
Threshold effect test.

Threshold variable	Number of thresholds	Threshold value	*P*-value	F-value	Threshold value		
					1%	5%	10%
ln*agg*	Single Threshold	0.191	0.100	17.90*	32.343	20.213	17.689
	Double Threshold	0.170	0.117	9.91	16.050	13.737	10.364

Note: *, **, and *** indicates statistical significance at 10%, 5%, and 1% levels, respectively.

Table 8
Estimation results of the threshold effect.

Variables	Estimation results	Confidence interval
ln*agg* (ln*agg*≤0.191)	0.024***(0.008)	[0.008, 0.040]
ln*agg* (ln*agg* > 0.191)	0.008 (0.012)	[-0.015, 0.032]
constant	−0.147 (0.309)	[-0.755, 0.461]
Control variable	yes	yes
City fixed effect	yes	yes
Year fixed effect	yes	yes
R^2	0.309	
Obs	4777	

Note: Standard errors in parentheses, *, **, and *** indicates statistical significance at 10%, 5%, and 1% levels, respectively.

later stage of agglomeration, vicious competition may occur among industrial enterprises to compete for limited factor resources, which ultimately hinders the improvement of ICP. However, according to the regression data, only 70 cities have crossed the threshold value, accounting for about a quarter of the sample size.

5.3. Analysis of differences in conduction mechanisms

According to the results of the threshold test, we divided the sample into two groups: cities with low industrial agglomeration levels (211 cities) and cities with high industrial agglomeration levels (70 cities). Table 9 reports the findings of the mediating and moderating effects tests for the low industrial agglomeration cities. The results indicate the presence of mediating effects for technological progress and labor mismatch, as well as moderating effects for environmental regulations in these cities. Table 10 reports the findings of the mediating and moderating effects for cities with high industrial agglomeration. In contrast to the low agglomeration cities, the mediating and moderating effects were not observed in the high agglomeration cities, as the impact of industrial agglomeration on ICP did not pass the 10% significance test. Furthermore, the promotion effect of low industrial agglomeration cities on technological progress is found to be more significant compared to high industrial agglomeration cities. This is related to the fact that low agglomeration cities are relatively backward in terms of economic development and science and technology, so that the marginal effect of industrial agglomeration on technological progress is higher. On the other hand, high agglomeration cities have already reached a mature and stable technological level, with fierce competition among enterprises and stronger awareness of intellectual property protection. Consequently, it is more challenging for industrial enterprises in high agglomeration areas to achieve significant technological progress. Considering that technological progress is a key driver of productivity growth [72–74], the significantly higher effect of agglomeration on technological progress in low-industrial agglomeration cities compared to high-industrial agglomeration cities is one possible explanation for the non-linear relationship between agglomeration and ICP.

6. Conclusions and policy recommendations

The present study investigates the correlation between industrial agglomeration and ICP and examines the underlying mechanisms by constructing mediating and moderating effect models using a sample of 281 cities in China from 2004 to 2020. The main findings are as follows: (1) The baseline regression results show that industrial agglomeration can significantly increase ICP. (2) Industrial agglomeration indirectly increases ICP through technological progress and labor mismatch reduction. Environmental regulations have a negative moderating role in the relationship between industrial agglomeration and ICP. (3) Further analysis reveals a threshold effect of industrial agglomeration on ICP. When the level of industrial agglomeration is below the threshold, there is a positive impact on ICP. However, when the level of industrial agglomeration exceeds the threshold, the impact becomes statistically insignificant. One possible explanation for this non-linear relationship is that low industrial agglomeration areas have a more significant impact on enhancing technological progress compared to high industrial agglomeration areas.

Table 9
Test results of mediating and moderating effects for cities with low-industrial agglomeration.

Variables	ln*t*	ln*icp*	ln*kmis*	ln*icp*	ln*lmis*	ln*icp*	ln*icp*
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ln*agg*	0.132**	0.019***	0.051	0.020***	−0.606***	0.019**	0.015*
	(0.057)	(0.006)	(0.067)	(0.006)	(0.059)	(0.006)	(0.008)
ln*t*		0.005***					
		(0.002)					
ln*kmis*				−0.000			
				(0.002)			
ln*lmis*						−0.004***	
						(0.001)	
ln*agg* × ln*er*							−0.017*
							(0.010)
constant	−15.483***	−0.364*	−5.747***	−0.449**	4.166**	−0.440**	−0.439**
	(1.790)	(0.198)	(2.107)	(0.196)	(1.863)	(0.196)	(0.196)
Control variable	yes	yes	yes	yes	yes	yes	yes
City fixed effect	yes	yes	yes	yes	yes	yes	yes
Year fixed effect	yes	yes	yes	yes	yes	yes	yes
R^2	0.674	0.334	0.039	0.333	0.055	0.333	0.333
Obs	3587	3587	3587	3587	3587	3587	3587

Note: Standard errors in parentheses, *, **, and *** indicates statistical significance at 10%, 5%, and 1% levels, respectively.

Table 10
Test results of mediating and moderating effects for cities with high-industrial agglomeration.

Variables	ln*t*	ln*icp*	ln*kmis*	ln*icp*	ln*lmis*	ln*icp*	ln*icp*
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ln*agg*	0.214 (0.148)	0.028 (0.020)	0.106 (0.153)	0.029 (0.020)	−0.541*** (0.156)	0.025 (0.020)	0.022 (0.028)
ln*t*		0.010** (0.004)					
ln*kmis*				0.007 (0.004)			
ln*lmis*						−0.008** (0.004)	
ln*agg* × ln*er*							−0.020 (0.053)
constant	0.873 (1.525)	0.315 (0.203)	−2.114 (1.573)	0.338* (0.204)	4.718*** (1.607)	0.361* (0.204)	0.332 (0.205)
Control variable	yes	yes	yes	yes	yes	yes	yes
City fixed effect	yes	yes	yes	yes	yes	yes	yes
Year fixed effect	yes	yes	yes	yes	yes	yes	yes
R^2	0.761	0.300	0.103	0.298	0.063	0.299	0.297
Obs	1190	1190	1190	1190	1190	1190	1190

Note: Standard errors in parentheses, *, **, and *** indicates statistical significance at 10%, 5%, and 1% levels, respectively.

Based on these findings, the present study proposes the following policy recommendations. Firstly, industrial agglomeration can significantly improve ICP, but excessive agglomeration will hinders the increase of ICP. Therefore, governments can attract industrial firms by providing policy support in the form of tax breaks in cities with low industrial agglomeration, as well as improved infrastructure and intermediate services. To play the important role of industrial agglomeration in improving ICP.

Secondly, considering that industrial agglomeration can enhance ICP by increasing technological progress and reducing labor mismatch. The Government can encourage exchanges and cooperation among enterprises within industrial agglomerations or between industrial agglomerations to promote the free flow of capital, labor and other factors of industrial production. In addition, emphasis should be placed on the interaction of highly skilled human capital in the industrial sector as well as green technologies to enhance the learning effect of industrial agglomeration.

Finally, considering the negative moderating effect of environmental regulations on the relationship between industrial agglomeration and ICP. Governments can provide certain incentives through fiscal and tax policies, such as financial subsidies or tax incentives for enterprises that adopt energy-saving and emission-reduction measures, so as to alleviate the cost of emission reduction and promote enterprises to improve ICP.

The study limitation and future directions include:

According to the economic theory of agglomeration, agglomeration involves learning, matching and sharing effects. However, the sharing effect at the industrial sector level is difficult to quantify and data are hard to obtain. Therefore, the empirical research part of this paper only quantitatively discusses the learning effect and the matching effect, and future research can further quantify the sharing effect at the industrial sector level to enrich the research mechanism in this field.

The datasets used during the current study are available from the corresponding author on reasonable request.

CRediT authorship contribution statement

Shujie Yao: Conceptualization, Formal analysis, Validation. **Xiaoqian Zhang:** Conceptualization, Writing – review & editing, Methodology, Data collection. **Weiwei Zheng:** Conceptualization, Data collection. **Jing Fang:** Conceptualization, Writing – original draft.

Declaration of competing interest

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.

Data availability

Data will be made available on request.

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