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The impact of structural upgrading of the service industry on regional ecologicalization efficiency of Industry: Empirical evidence from 30 Chinese provinces

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ABSTRACT

With the wave of the digital economy and industrial ecological construction, it is more essential for developing countries to focus on improving the structural quality of the service industry rather than just the quantitative aspect of the service industry. This study utilizes panel data from 30 provinces in China and spatial Dubin models to estimate the impact of service industry structure upgrading on industrial ecologicalization efficiency and its spatial effect. Our results reveal that productive and high-end service industries play a vital role in promoting industrial ecological efficiency. At the level of spatial effect, the productive service industry has a negative spatial correlation with the adjacent area, while the effect of the high-end service industry on the adjacent area is not highlighted. This study focuses on clarifying the spatial role of service industry structure upgrading on the improvement of industrial ecological efficiency, further expanding the theory of industrial structure adjustment, and providing insights for developing countries on how to optimize the structure of the service industry and achieve high-quality development of industrial ecologicalization.

1. Introduction

Sustainable development has emerged as a key concept in economic development in recent years. Developed countries, such as the United States, Germany, and Denmark, have recognized the importance of industrial ecology theory and practice. At the 10th International Conference on Industrial Ecology in 2019,the participants called for developing industrial ecologization and serving the construction of ecological civilization [1]. This emphasized the vital role of industrial ecologicalization in achieving a balanced development of ecology and economy [2]. Moreover, the emergence of the digital economy has increased the importance of the service industry. The outline of China's "14th Five-Year Plan" states that it is necessary to accelerate the development of modern service industries and promote productive service industries to specialize and reach the high-end of value chains. However, according to the China Statistical Yearbook 2022, China's service industry accounted for only 53.3 % of GDP in 2021. This is still considerably lower than the level of developed countries, which is around 70 %. This indicates that China's service industry development lags behind the modern economic development level, and that there is a need for further exploration and application of high-end elements for modern service industry development.

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China's secondary industry has been the main driver of its rapid economic growth in the 21st century, but it has also caused severe ecological degradation (Zafar et al., 2020) [3]. The government and scholars have realized the importance of the service industry for industrial ecology, which means that increasing the share of the service industry in the national economy can improve the efficiency of industrial ecology. This is crucial for China to optimize its industrial structure and overcome the challenge of high-quality economic development (Kang & Feng, 2016; Zhu et al., 2021) [4,5]. Many empirical studies have examined the impact of industrial structure upgrading on sustainable economic development, and they have confirmed that industrial structure upgrading has a positive effect on economic performance. Liu & Wei (2020) showed that industrial structure upgrading and green economic development are mutually reinforcing [6]. Zhang et al. (2022) revealed that agricultural industry agglomeration and industrial structure upgrading have a non-linear relationship with sustainable agricultural development [7].

Most studies on industrial structure upgrading focus on the quantitative aspects of the service industry share, but neglect the structural changes within the service industry. This overlooks the quality issue of industrial upgrading. The service industry, especially the high-end service industry, plays an important role in improving the quality and efficiency of traditional industries, such as the low-carbon transformation of high-pollution industries (Carlos et al., 2021; Yang et al., 2023) [8,9]. A typical research hotspot is the role of the digital economy in the green development of enterprises and regions. Li et al. (2022) showed that the digital transformation of enterprises can significantly reduce pollution emissions using the DID model [10]. Moreover, high-end service industries can also enhance the economic performance of enterprises and regions through industrial integration with manufacturing industries (Frank et al., 2019) [11]. Rob and John (2023) presented a case study to show how data analytics on manufacturing equipment can improve reliability and reduce maintenance costs [12]. Therefore, to estimate the effect of industrial restructuring on regional industrial eco-efficiency accurately, it is necessary to examine the structure of the service industry and use indicators that can reflect its internal structural upgrading. This will also help to explore the optimal path of service industry structure upgrading for industrial ecology improvement.

With the intensification of the greenhouse effect and rising labour costs, China's regional economic development is facing both ecological and production challenges, and the traditional extensive economic growth model is no longer sustainable (Guan et al., 2023) [13]. In 2020, the Chinese government also timely put forward the "3060″ dual-carbon target, encouraging and promoting the development of a low-carbon and circular economy (Wang et al., 2023) [14]. To accelerate the low-carbon transformation of the regional economy, provinces and municipalities need to adjust their industrial policies according to their regional positioning to maintain ecological and economic competitiveness (Johnstone et al., 2021; Xiong et al., 2023) [15,16]. Therefore, it is of great economic significance to study how to adjust the structure of the service industry to enhance the ecological efficiency of the industry. Moreover, previous studies have overlooked the spatial spillover effects of service sector structural upgrading on industrial ecologization, which may affect the accuracy of the estimation results. As suggested by Li & Wang (2022), carbon emissions trading has spatial spillover effects on carbon emission reduction [17]. Therefore, it is necessary to consider the potential spatial effects of structural upgrading in the service industry.

Based on this, this study, using panel data from 30 regions in China, takes the provincial productive service industry and high-end service industry as the research object, analyses in-depth the impact of different directions of upgrading the service industry structure on industrial eco-efficiency, and applies spatial econometric models to estimate the potential spatial effects. It provides policy insights for improving the quality of regional service industries and industrial eco-efficiency from a spatial perspective and helps to explore the realistic path of low-carbon transformation in the regional economy.

This study is closely related to Wang et al. (2023), who found that industrial upgrading significantly and positively affects industrial eco-efficiency using a panel data model [18]. In comparison, this study differs from theirs in the following aspects: (1) Focusing on the structural upgrading of the service sector, measured in terms of employment structure. (2) Unlike some productive service industry studies, this study also focuses on the agglomeration level of the high-end service industry and conducts comparative analyses (Liu et al., 2022; Li et al., 2022) [19,20]. (3) It enriches the research on the spatial effect of industrial upgrading on eco-efficiency. Therefore, in order to fill the research gap, this study takes the provincial productive service industry and high-end service industry as the research object, analyses the impact of industrial structure upgrading on eco-efficiency from a more nuanced industrial perspective, explores the relevant optimization practice paths, and ultimately makes certain research contributions.

2. Literature review and research hypothesis

2.1. Industrial upgrading and eco-efficiency

Since direct studies on the structural upgrading of services and industrial ecological efficiency are scarce, the literature search extends to the fields of industrial upgrading and ecological efficiency. Previous studies on the impact of industrial upgrading on eco-efficiency present the following distributional features: (1) In terms of research perspectives, the focus is on upgrading changes at the levels of industrial structure, industrial agglomeration, and industrial convergence and their impact on regional eco-efficiency. Industrial upgrading is a long-lasting process of industrial chain optimization, and the proportion of industrial structure, the degree of industrial agglomeration, and the degree of industrial integration can better reflect the dynamic changes of industrial upgrading. Industrial structure upgrading is usually regarded as an important path for the green transformation of regional economies, while environmental policy and technological innovation are important driving forces for industrial upgrading (Du et al., 2021; Chen et al., 2022; Xie et al., 2022) [21–23]. More empirical studies have examined the influence mechanism of industrial agglomeration, technological progress, and eco-efficiency and affirmed the green effect of industrial agglomeration, but the non-linear results have also shown the congestion effect of industrial agglomeration (Zheng et al., 2022; Wu et al., 2022; Zhang et al., 2023) [24–26]. Industrial integration empowers traditional industries through information technology and digital management, which can have a positive effect on the green development of traditional manufacturing industries (Feng et al., 2021; Liu et al., 2023; Meng et al., 2023) [27–29].

(2) The factor ratio of capital and labour and the share of services in GDP are more common measures of industrial upgrading. Industrial upgrading shifts industries with low resource allocation efficiency to knowledge-intensive or technology-intensive industries with higher allocation efficiency, reflecting changes in factor inputs such as capital, labor, and technology from the input perspective and changes in the output value of industrial structure from the output perspective (Hu et al., 2023) [30]. Yu et al. (2014) empirically tested the role of capital deepening in promoting industrial structure transformation based on the factor ratio of capital and labour [31]. Xiong Chuntao (2021) improved the output value proportion method by using the product of output value proportion and labour productivity of each industry to measure the level of industrial structure upgrading, and found that industrial upgrading played a mediating role in the path of financial agglomeration's impact on green development [32]. Shen et al. (2022) empirically estimated the impact of digital finance on industrial structure upgrading by using industrial rationalization and the share of tertiary industry in GDP to portray the level of industrial structure upgrading [33]. In addition, panel data models and synergistic coupling models are widely used by empirical analyses (Wang Q. et al., 2023; Zhang et al., 2023) [34,35].

(3) The impact of industrial upgrading on eco-efficiency varies across studies. Currently, industrial change led by digitalization and artificial intelligence has led to a consequent change in employment and industrial structure, and this potential impact is then transferred to eco-efficiency. On the one hand, digital empowerment of traditional industries attracts innovative and highly skilled talents and drives technological innovation in enterprises, which in turn enhances eco-efficiency. Ma et al. (2022) argued that AI increases the demand for middle- and higher-skilled labour, and the level of technology is rapidly advanced [36]. Yang (2022), based on micro-data from Taiwanese electronics industry enterprises, analysed that AI technology increased the proportion of labour force above the university level and promoted employment and productivity [37]. On the other hand, the existence of the "digital divide" makes it difficult for a limited employment group to reverse the regional industrial pattern, thus reducing the transmission effect of eco-efficiency. Su et al. (2022) found that industrial structure upgrading inhibited the green development of the region and retarded the sustainable development of the neighboring regions through the absorption of high-level talents and the transfer of pollution [38]. Arif et al. (2023) Arif et al. (2023) argued that the digital transformation of the economy created barriers to employment for people with disabilities [39]. Sun et al. (2023) argued that although AI can bring benefits to the industrial sector in high-productivity countries in the medium term, it will ultimately crowd out employment in the service sector, and therefore governments and businesses should avoid blindly promoting smart strategies [40].

In summary, although current research has confirmed that industrial structure upgrading is conducive to enhancing regional industrial eco-efficiency, it has hardly tested the spatial effect of industrial upgrading on eco-efficiency from the perspective of service industry structure. It has also not revealed the unique role of modern service industries on eco-efficiency in the digital economy era, in particular the difference in the effect of the productive service industry and the high-end service industry. In addition, to measure industrial upgrading, this study measures regional industrial upgrading in a more micro way through the employment structure of the service industry, replacing the traditional macro measurement of the tertiary industry as a share of GDP, which helps to estimate the spatial spillover effect of the modern service industry on eco-efficiency. Therefore, this study first measures the structural upgrading of services and industrial eco-efficiency in 31 provinces in China, then empirically tests the impact of structural upgrading of services on industrial eco-efficiency, and further reveals the existence of spatial effects and differences in their impacts.

2.2. Theoretical framework and research hypothesis

In response to the above research gaps, this study attempts to explore the impact of service industry structural upgrading on industrial ecological efficiency through the employment expansion of productive and high-end service industries. It also clarifies the logical relationship between service industry structure upgrading and regional eco-efficiency, as shown in Fig. 1.

The structural upgrading of the service industry is clearly characterized by the expansion and even agglomeration of the productive service industry and the industrial convergence in the high-end service industry. The productive service industry and high-end service

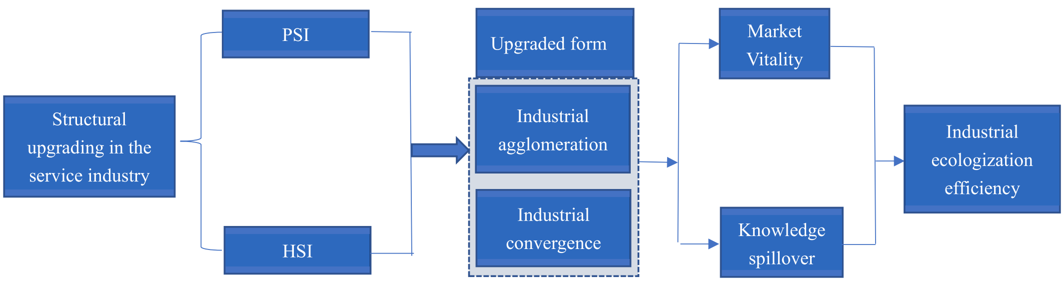

Fig. 1. Theoretical framework of the impact of structural upgrading in the service industry on industrial ecologization efficiency.

industry jointly cultivate and promote industrial upgrading, which triggers the resource flow to eco-efficient industries. This facilitates the flow of information, capital, technology, and talent, which reduces transaction costs and stimulates market vitality (Yang et al., 2018; Zeng et al., 2021) [41,42]. The influence of market dynamics on the efficiency of industrial ecology is mainly due to three effects: first, the factor flow effect. Productive service industry agglomeration promotes the interregional flow of economic resources, especially capital and talent, which optimizes resource allocation and corrects factor mismatch. Second, the market-competition effect. The agglomeration of the productive service industry intensifies the market competition in enterprise operations within and between regions, and under the incentive of environmental policy, it encourages enterprises to optimize operation and management, improve production technology, and ultimately enhance the competitive advantage of regional industry and green development efficiency. Third, the effect of economies of scale. The agglomeration of productive services forms economies of scale, which brings positive externalities to regional industries by reducing manufacturing production costs and intermediate transaction costs, and promotes the high-quality development of the regional economy. The three effects reflect the economic interaction between regions, so the productive services industry may have spatial effects on eco-efficiency. Based on this, hypotheses 1 and 2 are proposed.

Hypothesis 1. The productive service industry has a positive impact on regional industrial ecologization.

Hypothesis 2. The productive service industry can promote the development of industrial ecologization in neighboring regions through spatial spillover effects.

Industrial convergence in the high-end service industry contributes to the green transformation of the manufacturing industry through knowledge spillovers. The impact of knowledge spillover on the efficiency of industrial ecologization is mainly through three effects: first, the information sharing effect. High-end service industry integration provides a good channel of business learning for employees of manufacturing enterprises, reduces the asymmetry of market information, and makes the construction of an information sharing platform possible (Dong X et al., 2022) [43]. Second, the division of labour effect. The high-end service industry serves the manufacturing industry with advanced technology and management knowledge, improves the industrial chain efficiency and collaboration, makes manufacturing production more specialized and refined, and leads the industry to the high end of the value chain (Harris &Fleming, 2017) [44]. Third, the science and technology innovation effect. The high-end service industry integration facilitates the flow of technology and human resources, especially digital intelligent technology, accelerates inter-industry technological cooperation, promotes enterprise innovation, and transforms the manufacturing industry to low-carbon (Henrik & Rita, 2021) [45]. These effects suggest that the knowledge spillover of high-end service industry may drive inter-regional industrial technological cooperation and cleaner production transformation, so there may be a spatial effect of high-end service industry on eco-efficiency. Hypotheses 3 and 4 are proposed accordingly.

Fig. 2. China's four major economic regions in this study.

Hypothesis 3. High-end services play a positive role in the efficiency of regional industrial ecology.

Hypothesis 4. There is a spatial spillover effect of high-end services on the efficiency of industrial ecologization in the surrounding areas.

3. Data and methodology

3.1. Structure upgrading of the service industry

The structure of the service industry often reflects the development trend of a certain region's service industry through the economic quantity relationships of various industries within the service industry, such as structural optimization or lagging development. According to research, efficient and productive service industries are crucial in supporting both advanced manufacturing and modern agriculture, particularly in areas such as information, technology, and logistics (Marcu et al., 2020; Yu et al., 2022) [46,47]. As a result, the development of these service industries plays a significant role in upgrading the economic structure and promoting high-quality development, and to some extent represents the optimization level of service industry structure. Due to the heterogeneity of the internal structure in the service industry, this study mainly refers to the China Statistical Bureau's classification standard (2015) [48], which divides the service industry into two categories: productive service industry and non-productive service industry according to the service object. Among them, productive service industries include transportation, warehousing and postal services, information transmission, computer services and software industries, finance, leasing and business services industries, scientific research, technical services and geological exploration industries. Non-productive service industries include water conservation, environmental and public facilities management industries, the education industry, health care, social security and social welfare industries, cultural, sports and entertainment industries, public management and social organizations, wholesale and retail industries, accommodation and catering industries, the real estate industry and resident services. Borrowing from Yu & Yan (2019) [49], this study selects the ratio of employees engaged in productive service industries to total employees in service industries (hereinafter referred to as 'PSI') as one of its core explanatory variables to describe China's dynamic changes in service industry structure.

According to the classification of China's economic regions by the National Bureau of Statistics, 31 provinces and cities fall under four major regions, namely, the eastern region, the central region, the western region, and the northeastern region. However, the Tibet region has not been included in this study area due to inadequate data, as depicted in Fig. 2. Fig. 3 highlights the changes in PSI value across China's major economic regions from 2007 to 2018. The figures demonstrate that the Service1 value of all four regions has remained on a stable upward trend, particularly after 2011. Notably, the productive service industry's percentage in the eastern region has consistently remained higher than in the other regions, with a peak of 34.82 % in 2017. It is imperative to mention that the northeastern region has also maintained a relatively high proportion of productive service industries, mainly due to the absorption of the local labor force by the transportation industry.

As the transportation, warehousing, and postal industries encompass certain living functions, it is crucial to assess the robustness of the impact of service structure upgrading on industrial ecologicalization efficiency. Additionally, verifying the effect of service structure upgrading on maintaining regional industrial ecology and efficiency balance is important. Consequently, this study has selected the ratio of employees engaged in high-end service industries to total employees in service industries (hereinafter referred to as 'HSI') as another core explanatory variable. To classify the high-end service industry, the authors have referred to Pan & Zhou's (2021) classification and considered data availability [50]. Accordingly, "information transmission, computer services and software industry", "financial industry", "leasing and business services industry", and "scientific research, technical services and geological exploration industry" have been chosen as four categories to represent the high-end service industry. Fig. 4 depicts the change in HSI value in China's four major economic regions from 2007 to 2018. The proportion of employment in the high-end service industry has witnessed a weak upward trend in the four major regions, as highlighted in Fig. 3. Notably, the eastern region has a much higher Service2 value than other regions, with a maximum value of 25.81 % in 2017. It is reliable to infer that China's current service structure development lags behind that of Western developed countries, and there is still a considerable gap from the standard of 70 % (the proportion of output value of the productive service industry to the total output value of the service industry), with the service industry in the eastern region being more developed. In contrast, the service industry in the central and western regions is at roughly the same backward level, primarily due to their greater economic efficiency in agriculture and manufacturing.

3.2. Entropy value method

The concept of "industrial ecological efficiency" distinguishes itself from conventional regional economic performance evaluations by emphasizing the equilibrium between regional industrial economy and industrial ecology. A vital method of measuring the industrial ecological efficiency of a region involves selecting specific indicators that can effectively analyze industrial input and output dimensions. This study has identified twelve specific indicators, which are outlined and detailed in Table 1. The assessment of industrial input considers multiple factors, such as investment in fixed assets, labor, land, water resources, and expenses on environmental protection and governance. Additionally, the assessment indicators of industrial output evaluate the economic and ecological benefits generated by regional industries, such as GDP, carbon emissions, and industrial waste.

The current study employs the entropy value method and the linear weighting function method to gauge industrial ecologicalization efficiency. With consideration of the indicator data, the corresponding weight levels are objectively established to serve as the foundation for multi-index evaluation systems. The precise mathematical formula for computation is presented as follows:

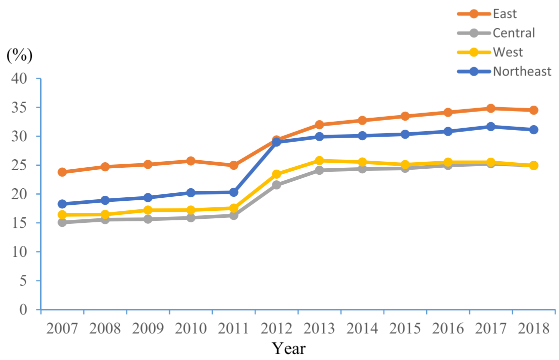

Fig. 3. The ratio of productive services in China's four major economic regions from 2007 to 2018.. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

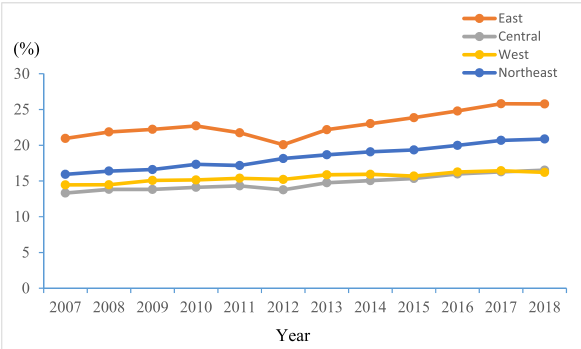

Fig. 4. The ratio of the high-end service industry in China's four major economic regions from 2007 to 2018.. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

$$
\begin{aligned}
e_j &= -\frac{1}{ln\,(n)}\sum_{i=1}^{n}\frac{X_{ij}}{\sum_{i=1}^{n}X_{ij}}ln\frac{X_{ij}}{\sum_{i=1}^{n}X_{ij}}\\
w_j &= 1-\frac{e_j}{\sum_{i=1}^{n}(1-e_j)}\\
Y_{it} &= \sum_{j=1}^{n}w_j\times\frac{X_{ij}}{\sum_{i=1}^{n}X_{ij}}
\end{aligned}
\tag{1}
$$

In equation (1), X_{ij} is the index matrix after nondimensionalization, e_j is the entropy value of the j-th index, w_j is the index weight determined by information entropy, and Y_{it} is the industrial ecological efficiency of region i in year t.

[1]The industrial ecological efficiency level of the top five and bottom five provinces in 2018 is depicted in Fig. 4. As illustrated in Fig. 5, the provinces in the front of the regional industrial ecologicalization efficiency calculated by the entropy method are mainly located in the eastern region. Jiangsu exhibited the highest industrial ecological efficiency level of 0.4165. Conversely, provinces with comparatively underdeveloped regional industrial ecologicalization efficiency are predominantly located in the western and north-eastern regions.

3.3. The design of the space panel model

The present study centers on analyzing the effects of structural upgrading in the service industry on industrial ecology efficiency. It incorporates a consideration of the spatial dimension regarding industrial ecology efficiency, with taking into account the analysis dimensions of region and time. Therefore, empirical analysis is conducted employing a spatial panel model. The regression model employed is designed as follows:

[1] From left to right, the provincial abbreviations correspond to Jiangsu, Beijing, Guangdong, Shandong, Hainan, Liaoning, Jilin, Gansu, Ningxia, and Shanxi.

Table 1
Evaluation system of regional industrial ecologicalization efficiency index.

Index layer	Indicator description
Investment in fixed assets	Construction and acquisition of fixed assets
Total energy consumption of industry	Total energy consumption of three industries
Employed population	Rural and urban employment
Total industrial utilization of water	Water consumption for production
Construction land area	Urban industrial and commercial land area
Regional environmental expenditure	For environmental protection and governance
GDP per capita	GDP divided by population
Utilization rate of industrial waste	Ratio of waste utilization to waste volume
Carbon emission	Reciprocal processing
Industrial wastewater	Reciprocal processing
Industrial sulfur dioxide	Reciprocal processing
Industrial waste	Reciprocal processing

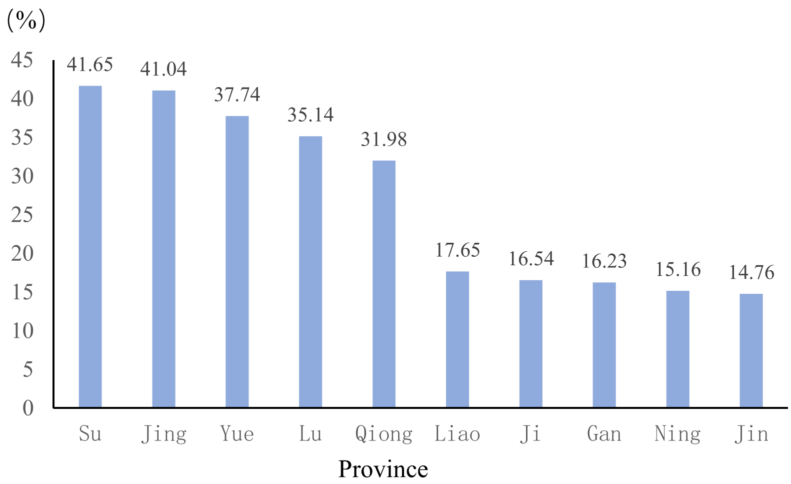

Fig. 5. Ranking of the front and rear stages of industrial ecological efficiency in 2018.

$$\begin{aligned} Y_{it} &= \beta_1 SER1_{it} + \beta_2 CON_{it} + \delta_i + \mu_t + \varepsilon_{it} \\ Y_{it} &= \beta_1 SER2_{it} + \beta_2 CON_{it} + \delta_i + \mu_t + \varepsilon_{it} \\ Y_{it} &= \rho W_k Y_{it} + \beta_1 SER1_{it} + \beta_2 CON_{it} + \theta_1 W_k SER1_{it} + \theta_2 W_k CON_{it} + \delta_i + \mu_t + \varepsilon_{it} \\ Y_{it} &= \rho W_k Y_{it} + \beta_1 SER2_{it} + \beta_2 CON_{it} + \theta_1 W_k SER2_{it} + \theta_2 W_k CON_{it} + \delta_i + \mu_t + \varepsilon_{it} \end{aligned} \tag{2}$$

In equation (2), Y_{it} is the industrial ecologicalization efficiency of region i in year t, CON_{it} is the control variable group, δ_i is the cross-sectional individual difference of each province and city that does not change with time, μ_t is the time effect, and ε_{it} is the random error term. W_k ($k = 1,2$) represents the spatial weight matrix. Table 2 is an explanation for the symbols of each variable in the model. Table 3 illustrates how the model variables are calculated.

In the spatial effect analysis, the explained variable is the industrial ecologicalization efficiency. Considering the similarity of adjacent geographical conditions and ecological environments, 0–1 adjacency weight matrix (W1) is selected. Given that the industrial ecologicalization efficiency involves industrial economic matters, a straightforward geographical distance matrix may not fully reflect the spatial correlation. Therefore, it is necessary to further use the economic geographic spatial weight matrix (W2), which essentially considers the dual effects of geographic distance and economic distance. This also contributes to enhancing the robustness of the model estimates. The W2 matrix calculation process is as follows:

$$\begin{aligned} W_2 &= w_{ij} \times diag\left(\frac{\overline{E_1}}{\overline{E}}, \frac{\overline{E_2}}{\overline{E}}, \ldots, \frac{\overline{E_n}}{\overline{E}}\right) \\ w_{ij} &= \begin{cases} \frac{1}{d_{ij}^2}, i \neq j \\ 0, i = j \end{cases} \end{aligned} \tag{3}$$

Table 2
description of model variables.

Variable	Variable name	Variable symbol
Explained variable	Industrial ecologicalization efficiency	Y_{it}
Explanatory variables	Productive services	PSI
	High-end service industry	HSI
Control variable	Structure of energy consumption	E
	Level of foreign investment	F
	Industrial scale	I
	Population density	lnP
	Level of state-owned economy	lnN
	Contamination treatment	lnC

Table 3
description of variable symbols.

Variable symbol	Variable illustration
Y_{it}	Estimated by entropy method
PSI	The proportion of employees in productive service industry (%)
HSI	The proportion of employees in high-end service industry (%)
E	The ratio of coal consumption to energy consumption (%)
F	The ratio of foreign direct investment to GDP (%)
I	The ratio of the secondary industry to GDP (%)
lnP	Number of people per square kilometer, logarithm value
lnN	State-owned economic income，logarithm value(100 million yuan)
lnC	Investment in industrial pollution control (10,000 yuan)

In equation (3), w_{ij} represents the geographical distance matrix, d_{ij} represents the geographical distance between region i and region j, $\overline{E_t} = \frac{\sum_{t_0}^{t_1} E_{it}}{t_1 - t_0 + 1}$, t=(1,2, …,n) represents the average value of the regional product during the period from t_0 to t_1, $\overline{E} = \frac{\sum_{i=1}^{n}\sum_{t_0}^{t_1} E_{it}}{n(t_1 - t_0 + 1)}$ represents the average GDP of all provinces during the period from t_0 to t_1, t represents the corresponding year, and n = 30 represents a total of 30 provinces.

3.4. Data sources

To avoid the impact of the COVID-19 outbreak on China's economic data and address the absence of statistical information from the Tibet Autonomous Region, this research utilized panel data sourced from 30 provinces across China spanning from 2007 to 2018. Data on industrial ecologization come from the China Statistical Yearbook and the China Environmental Statistics Yearbook; data on the employment structure of the service sector come from the China Population and Employment Statistics Yearbook; data on energy consumption come from the China Energy Statistics Yearbook; data on the amount of foreign direct investment, the size of industry and the size of the population come from provincial and municipal statistical yearbooks; data on the income of the state-owned economy come from the China State-Owned Assets Supervision and Administration Yearbook; and data on the amount of investment in industrial pollution control come from the China Environmental Statistics Yearbook. The descriptive statistical findings for the regression model variables have been presented in Table 4.

Table 4
Descriptive statistics of model variables.

Variable	Observation	Average	Standard deviation	Minimum	Maximum
Y_{it}	360	0.2102	0.0616	0.1146	0.4308
PSI	360	0.2455	0.0779	0.1310	0.5232
HSI	360	0.1811	0.0581	0.1117	0.4367
E	360	0.4263	0.1522	0.0163	0.7241
F	360	0.0224	0.0204	0.0001	0.1210
I	360	0.4579	0.0831	0.1863	0.5905
lnP	360	7.8416	0.4447	6.4329	8.6940
lnN	360	8.2007	1.0809	4.7825	10.4873
lnC	360	11.8624	0.9807	8.1784	14.1637

4. Empirical analysis results

4.1. Normality test and cross-sectional dependence test

Normal distribution is the basis of many test parameter estimations; thus, it is necessary to carry out the normality test first. The Jarque-Bera test is based on the skewness and kurtosis of the data samples to judge whether the samples conform to the overall normal distribution, which is suitable for large sample objects. Table 5 shows the results of the Jarque-Bera normality test. As can be seen from Table 5, the JB values of PSI and HSI are 115 and 62.19, respectively, and the corresponding P-values are less than 0.01, which indicates that the core variables PSI and HSI do not conform to the standard normal distribution, which also confirms that the absolute normal distribution is less likely to exist in reality. However, the absolute values of skewness and kurtosis of both PSI and HIS are less than 3, which indicates that the symmetry and smoothing of the data are better, and the data samples can be regarded as approximately normally distributed (Kline et al., 2011) [51]. Meanwhile, the intuitive diagram can also support this. As shown in Fig. 6, the histogram distribution of HSI, approximates the normal distribution curve. Therefore, PSI and HSI can be further tested.

Due to the economic interactivity among provinces such as industrial cooperation and population mobility, cross-sectional correlation cannot be ruled out, which may ultimately affect the accuracy of the estimation results. Drawing on the method of Li et al. (2022), this study uses Pesaran's (2004) CD test to examine cross-sectional correlation. The test results are shown in Table 6 [52,53]. In the CD test, the statistical P values of PSI and HIS are both less than 0.01, indicating the existence of cross-sectional correlation. Since the data has cross-sectional correlation, the ordinary unit root test method is invalid, so this study uses the CIPS test proposed by Pesaran, the second-generation unit root method, to test whether the sample data is stationary (Dou et al., 2021) [46]. As can be seen from Table 6, the CIPS results all show significance at the 1 % level, indicating that the PSI and HIS variables are stationary at the level, so the next step of panel data model parameter estimation can be carried out.

4.2. Baseline regression estimation

To reflect the overall level of the impact of structural upgrading of the service industry on the efficiency of industrial ecologicalization, OLS multilevel regression is used for benchmark estimation. The results of regression estimation under fixed regional and annual effects are presented in Table 7. To ensure the reliability of the estimation results, robust standard errors are used for regression in all models. The results show that a higher proportion of productive service industries is conducive to improving regional industrial ecologicalization levels, as indicated by the impact coefficient of 0.513 with statistical significance at the 1 % level, under the control of covariates. Moreover, the impact coefficient of 0.687 for the high-end service industry under the control of covariates indicates that it can significantly promote the improvement of industrial ecologicalization efficiency. Overall, the regression results demonstrate that structural upgrading of the service industry has a positive impact, not only on industrial economic efficiency but also on ecological environment protection. However, benchmark regression cannot test the spatial effects between variables, and further estimation using spatial econometric models is recommended.

4.3. Spatial correlation analysis

4.3.1. Global spatial autocorrelation test

Spatial correlation constitutes a crucial prerequisite in conducting econometric research on spatial effects. Two principal techniques exist for assessing spatial correlation: the global spatial autocorrelation test and the local spatial autocorrelation test. In empirical analysis, Moran's Index (Moran's I) stands out as a commonly employed technique for evaluating spatial correlation. The value of Moran's I assesses the extent of spatial correlation among adjacent areas of the study subject (Li & Zhou, 2021) [54]. The calculation formula for this test is as follows:

$$moran's\ I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\left[(Y_i - \overline{Y})(Y_J - \overline{Y})\right]}{S^2 \sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}}$$

In this equation, Y_i represents the observed value of variable Y in i province, and S^2 is the variance.

In the present study, the global Moran's I value of regional industrial ecologicalization efficiency was calculated using spatial matrices W1 and W2, as depicted in Table 8. Under the adjacency matrix W1, the Moran's I values of industrial ecologicalization

Table 5
Results of the Jarque-Bera normality test.

Variable	Skewness	Kurtosis	Jarque-Bera test	
			The value of statistic JB	P-value
PSI	1.142	1.619	115***	.000
HSI	−0.049	2.079	62.19***	.000

Note: *, **, ***mean significant at the 10 %, 5 %, and 1 % level respectively.

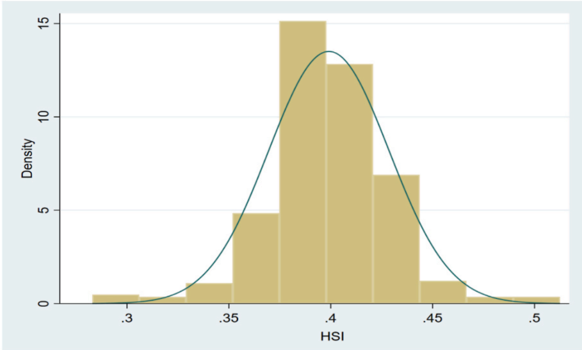

Fig. 6. Histogram distribution of the high-end service industry.

Table 6
Results of cross-sectional dependence test.

Variable	Pesaran CD Test		Pesaran CIPS Test-Level	
	Statistic	P-value	Intercept	Intercept and Trend
PSI	9.600***	.000	−3.040***	−3.167***
HSI	36.740***	.000	−2.351***	−3.364***

Note: *, **, ***mean significant at the 10 %, 5 %, and 1 % level respectively.

Table 7
The results of baseline regression estimation.

Variable	M1	M2	M3	M4
PSI	0.448***	0.513***		
	(0.108)	(0.089)		
HSI			0.692***	0.687***
			(0.125)	(0.104)
E		−0.143***		−0.123***
		(0.027)		(0.024)
F		0.634***		0.586***
		(0.115)		(0.101)
I		0.065**		0.024
		(0.034)		(0.032)
lnP		−0.003		−0.001
		(0.006)		(0.006)
lnN		0.007		0.011*
		(0.006)		(0.006)
lnC		−0.002		−0.003
		0.003		(0.003)
Region fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Constant	0.095	0.093	0.064	0.055
Adjusted R^2	0.883	0.905	0.899	0.917
Observation	360	360	360	360

Note: ①* * *, * *, and * indicate significance at confidence levels of 1 %, 5 %, and 10 %, respectively; ②Robustness standard error is shown in parentheses.

efficiency were consistently positive, hovering around 0.3, and all results passed the 1 % significance test. This suggests that industrial ecologicalization efficiency exhibits a pronounced agglomeration tendency in spatial distribution, with the industrial ecologicalization efficiency of one province having the potential to impact neighboring provinces through spatial spillover effects. As for the economic geography spatial matrix W2, the Moran's I values of industrial ecologicalization efficiency exhibited an upward trend from 2007 to 2018, with an accompanying increase in significance level. This indicates a strong, positive spatial correlation between industrial ecologicalization efficiency and economic geographic factors.

4.3.2. Local spatial autocorrelation test

The global Moran's I offers insight into the overall agglomeration phenomenon of industrial ecologicalization efficiency on a country-wide scale. However, it may not provide an adequate explanation for the spatial correlation between provincial administrative

Table 8
Global Moran test results of industrial ecologicalization efficiency.

Year	W1		W2	
	Moran's I	P-value	Moran's I	P-value
2007	0.258***	0.002	−0.020	0.422
2008	0.278***	0.002	0.013	0.269
2009	0.320***	0.001	0.036*	0.085
2010	0.340***	0.001	0.074*	0.088
2011	0.344***	0.001	0.177***	0.007
2012	0.395***	0.000	0.134**	0.024
2013	0.343***	0.001	0.173***	0.008
2014	0.265***	0.007	0.183***	0.005
2015	0.332***	0.001	0.204***	0.003
2016	0.300***	0.003	0.211***	0.002
2017	0.319***	0.002	0.217***	0.002
2018	0.344***	0.001	0.205***	0.003

Note: * * *, * *, and * indicate significance at 1 %, 5 %, and 10 % confidence levels, respectively.

regions. Additionally, the local Moran's I can be used to accurately assess the spatial heterogeneity between regions through a scatter plot. A scatter plot of industrial ecologicalization efficiency, illustrated in Fig. 7(a), reveals that scatter points in each province predominantly fall within the first and third quadrants, with few in the second and fourth quadrants. This implies that industrial ecologicalization efficiency in this region is mostly characterized by "high-high agglomeration" or "low-low agglomeration", indicating a significant positive spatial spillover effect on the development level of adjacent regions. Notably, Fig. 7 (b) and 7 (c) together show that Shanghai, Zhejiang, Jiangsu, and Guangdong in the eastern coastal areas, Yunnan-Guizhou-Sichuan region, and Gansu-Ningxia in the western areas have demonstrated positive spatial spillover for their industrial ecologicalization efficiency in 2010 and 2018. However, Beijing and Qinghai have shown discrepant ecological industrialization efficiency levels with surrounding areas due to their relative economic and ecological advantages, indicating a "high-low agglomeration" spatial relationship. In conclusion, inter-provincial industrial ecologicalization efficiency exhibits both correlation and heterogeneity in spatial distribution.

4.4. Spatial econometric estimation results

The application of spatial econometric models, such as the Spatial Lag Model (SAR), the Spatial Error Model (SEM), and the Spatial Dubin Model (SDM), was determined by employing the LM, Hausman, and LR tests. The corresponding findings are presented in Tables 9 and 10. First, through the LM test under the W1 and W2 spatial matrices, the P values of the LM-error and LM-lag test statistics of the producer services industry are both less than 0.05, indicating that the producer services industry can be modeled using a spatial econometric model. Secondly, through the LR likelihood ratio test under the W1 and W2 space matrices, the model statistic tests of the producer service industry are all significant at the 1 % level, indicating that the SDM model cannot be simplified to a SAR or SEM model in model selection. Finally, through the Hausman test under the W1 and W2 space matrices, the model statistics tests of the producer services industry are all significant at the 1 % level, indicating that the producer services industry is suitable for the fixed effects model. Therefore, the spatial Dubin fixed effect model was chosen for the productive service industry. Correspondingly, from Tables 10 and it can be observed that the high-end service industries also opted for the spatial Dubin fixed effect model.

The fixed effect models comprise time-fixed effects, individual fixed effects, and time-individual double fixed effects. The selection of the optimal fixed effect spatial Durbin model was determined through a regression estimation of the three fixed effect models. The factors considered in the comparison included the goodness of fit R2, the log-likelihood value, and Sigma2, as presented in Table 11. Notably, individual fixed effects were applied in models (5), (6), and (8), while model (7) used time fixed effects.

From a holistic perspective, the result has shown that the spatial autoregressive coefficients of industrial ecologicalization efficiency in models (5) and (6) are statistically significant at the 5 % and 1 % confidence levels, with values of 0.1325 and 0.4323 respectively. This signifies that there is a positive spatial spillover effect with regards to regional industrial ecological efficiency, whereby an improvement in local ecologicalization efficiency also positively impacts the industrial ecologicalization of surrounding areas. This result highlights the intrinsic driving force of industrial ecologicalization development, which not only improves local productive efficiency and industrial environments, but also radiates to neighboring areas through the progress of industrial technology. Model (6) also asserts that the proportion of productive service industries has a significant role in promoting industrial ecological efficiency. A 1 % increase in the proportion of the productive service industry results in a 0.4322 % increase in industrial ecological efficiency. Simultaneously, in terms of spatial effects, the spatial lag regression coefficient for the productive services proportion results in −0.1845, whose significance at the 5 % confidence level demonstrates that an increased proportion of productive services in adjacent regions leads to the reduced ecologicalization efficiency of a region's industries. Such a phenomenon can be attributed to the competitiveness of the industrial economy. With significant advancements in the productive services development of neighboring areas, an influx of labor and consumer groups shall ensue, thereby posing a formidable challenge and menace on the region's industrial economic efficiency.

The spatial autoregressive coefficients of industrial ecological efficiency are 0.1071 and 0.3948 in model (7) and (8) respectively. These coefficients are significant at the 10 % and 1 % confidence levels through significance tests. This suggests a positive spatial

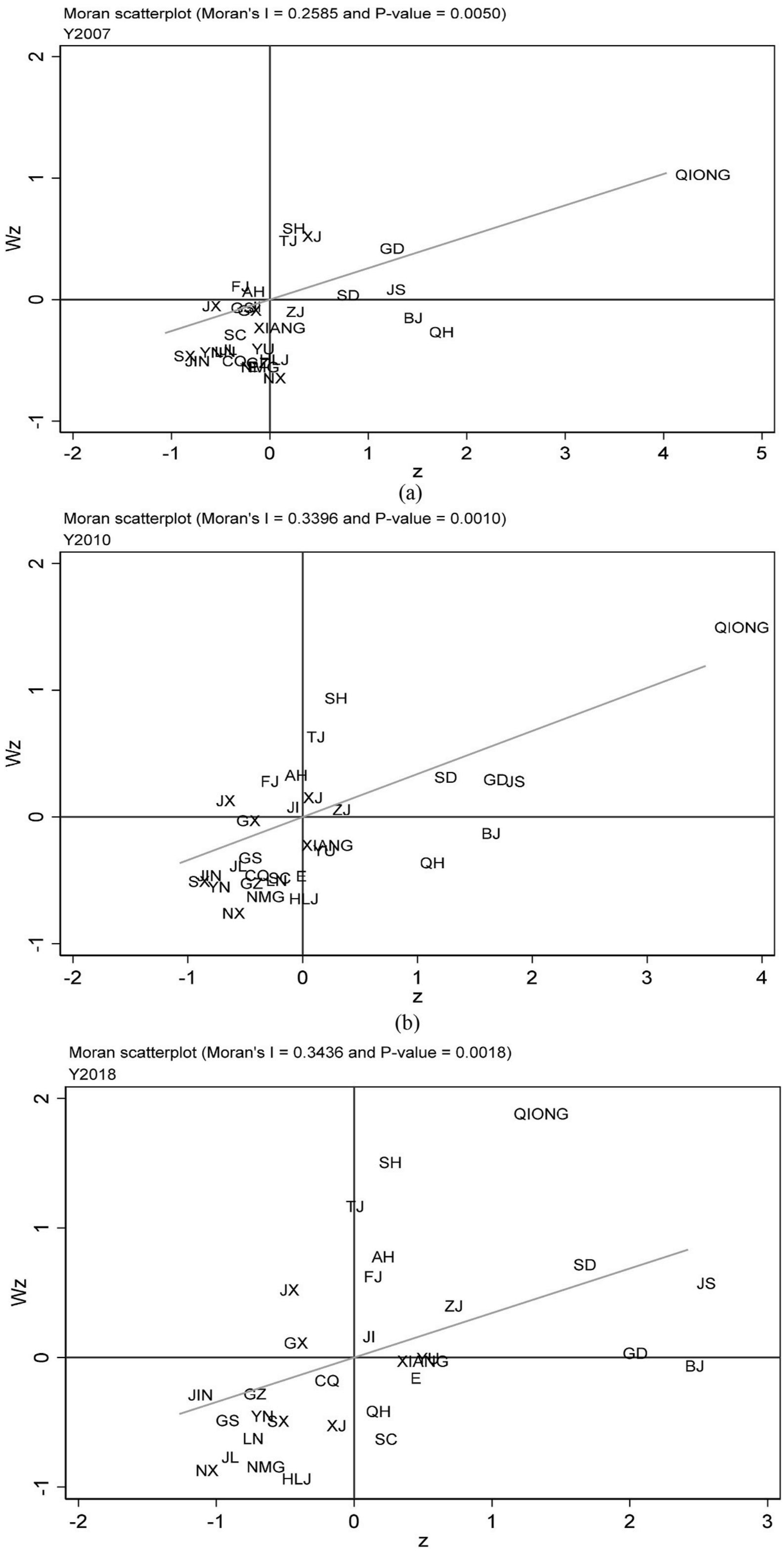

Fig. 7. Moran scatter diagram of industrial ecologicalization efficiency in 2007, 2010 and 2018. (a) The Moran scatter plot is described with the data on industrial ecologicalization efficiency in 2007; (b) The Moran scatter plot is described with the data on industrial ecologicalization efficiency in 2010; (c) The Moran scatter plot is described with the data on industrial ecologicalization efficiency in 2018.

Table 9
Spatial econometric model test for the productive service industry.

Test	W1		W2	
	Statistic	P-value	Statistic	P-value
LM-error	19.965***	0.000	18.378***	0.000
R-LM-error	10.035***	0.002	26.108***	0.000
LM-lag	15.659***	0.000	7.834***	0.005
R-LM-lag	5.729**	0.017	15.564***	0.000
Hausman	67.67**	0.026	85.38***	0.000
LR-Spatial-lag	57.25***	0.000	109.36***	0.000
LR-Spatial-error	60.08***	0.000	106.01***	0.000

Note: * * *, * *, and * indicate significance at 1 %, 5 %, and 10 % confidence levels, respectively.

Table 10
Spatial econometric model test for the high-end service industry.

Test	W1		W2	
	Statistic	P-value	Statistic	P-value
LM-error	22.408***	0.000	4.002**	0.045
R-LM-error	11.559***	0.001	8.237***	0.004
LM-lag	16.754***	0.000	10.063***	0.002
R-LM-lag	5.904**	0.015	14.298***	0.000
Hausman	22.76*	0.0894	45.57***	0.000
LR-Spatial-lag	49.71***	0.000	70.18***	0.000
LR-Spatial-error	53.33***	0.000	66.17***	0.000

Note: * * *, * *, and * indicate significance at 1 %, 5 %, and 10 % confidence levels, respectively.

correlation effect of industrial ecological efficiency, and indicates an obvious agglomeration phenomenon in regions with high levels of industrial ecological efficiency. Furthermore, model (8) reveals that the proportion of the high-end service industry has a significant promoting effect on industrial ecological efficiency. Specifically, the analysis indicates that a 1 % increase in the proportion of the high-end service industry leads to a 0.5880 % increase in industrial ecological efficiency. However, the spatial lag regression coefficient of the proportion of the high-end service industry is 0.0346, and its P value did not pass the significance test. In summary, a comparison of the results of four regression models suggests that the positive spatial spillover effect of industrial ecological efficiency has consistency, and that the productive service industry and the high-end service industry confirm the promotion effect of structural upgrading of the service industry on industrial ecological efficiency. Nonetheless, in terms of spatial effects, the high-end service industry shows inconsistency, which may be because of the current low development level of China's high-end service industry, and the lack of stimulation or threat from high-end service industries in adjacent areas for regional industrial ecologicalization.

The regression analysis indicates that the β_2 coefficient results for the control variables are relatively stable and consistent, mainly in energy consumption structure and foreign investment level. The data demonstrates that the proportion of coal consumption in energy utilization has a notable inhibitory impact on industrial ecological efficiency, whereas the level of foreign investment has a significant promoting effect on industrial ecological efficiency. These findings suggest that decreasing coal consumption and increasing foreign investment can contribute to China's regional industrial ecology improvement and greater economic benefits. Furthermore, the examination of spatial effects exhibits that adjacent areas' foreign investment levels and state-owned economic levels have negative spatial spillover effects on local industrial ecological efficiency, which indicates that foreign and state capital continue to play a significant role in regional economic competition and high-quality development.

To further analyze the differences in the impact of explanatory variables on industrial ecological efficiency and spatial spillover effects, it is essential to calculate the direct and indirect effects of each explanatory variable. The outcomes of this calculation can be found in Table 12 and Table 13. The direct effect of productive service industry on local industrial ecological efficiency stands out positively and significantly at a 1 % confidence level, which implies that the productive service industry can significantly encourage the enhancement of local industrial ecological efficiency. However, in model (5), the indirect effect of productive service industry on adjacent regional industrial ecological efficiency demonstrates a negative and significant association at a 10 % confidence level. This indicates that regional competition in the productive service industry may hinder the improvement of adjacent regional industrial ecological efficiency. On the other hand, the direct effect of the high-end service industry on local industrial ecological efficiency is positively significant at the 1 % confidence level, which implies that the high-end service industry can significantly boost local industrial ecological efficiency. However, when it comes to spatial effects, the high-end service industry does not present a significant impact on adjacent regional industrial ecological efficiency. This may indicate that the present quality of high-end service industry agglomeration in the region may be inadequate to produce positive spatial spillover effects.

Table 11
Estimation results of the spatial Dubin fixed effect model for the productive service industry and the high-end service industry.

Variable	M5	M6	M7	M8
	W1	W2	W1	W2
PSI	0.3821***	0.4322***		
	(6.26)	(7.20)		
HSI			0.5974***	0.5880***
			(9.64)	(9.37)
E	−0.1211***	−0.1314***	−0.0993***	−0.1083***
	(-4.84)	(-5.47)	(-4.16)	(-4.67)
F	0.6524***	0.6882***	0.6022***	0.6460***
	(6.38)	(6.78)	(6.24)	(6.58)
I	0.0159	0.1003***	−0.0104	0.0640**
	(0.45)	(2.91)	(-0.31)	(1.98)
lnP	0.0041	0.0010	0.0008	0.0036
	(0.60)	(0.15)	(0.12)	(0.57)
lnN	0.0015	0.0138***	0.0059	0.0187***
	(0.26)	(2.69)	(1.07)	(3.85)
lnC	−0.0036*	−0.0039*	−0.0028	−0.0035*
	(-1.79)	(-1.90)	(-1.52)	(-1.82)
W × PSI	−0.1758**	−0.1845**		
	(-2.22)	(-2.05)		
W × HSI			0.0763	0.0346
			(0.58)	(0.19)
W × E	−0.2595***	−0.0041	−0.1807***	0.0174
	(-5.66)	(-0.07)	(-4.03)	(0.29)
W × *F*	−0.7599***	−0.6700***	−0.6662***	−0.6577***
	(-2.79)	(-3.56)	(-2.59)	(-3.69)
W × *I*	0.1576***	−0.0795	0.1886***	−0.0341
	(3.16)	(-1.36)	(4.06)	(-0.60)
W × *lnP*	0.0046	−0.0043	−0.0061	−0.0157
	(0.34)	(-0.21)	(-0.49)	(-0.81)
W × *lnN*	−0.0126*	−0.0222***	−0.0014	−0.0137**
	(-1.76)	(-2.95)	(-0.22)	(-2.02)
W × *lnC*	0.0014	−0.0035	0.0075**	0.0063*
	(0.38)	(-0.79)	(2.50)	(1.94)
Spatial-rho	0.1325**	0.4323***	0.1071*	0.3948***
	(2.11)	(5.76)	(1.84)	(5.02)
Sigma^2	0.0003***	0.0003***	0.0003***	0.0002***
	(13.40)	(13.25)	(13.40)	(13.27)
R-squared	0.3409	0.2814	0.3725	0.2878
Observation	360	360	360	360

Note: * * *, * *, and * indicate significance at 1 %, 5 %, and 10 % confidence levels, respectively.

Table 12
Test results of direct and indirect effects of the productive service industry.

Variable	M5			M6		
	Direct	Indirect	Total effect	Direct	Indirect	Total effect
PSI	0.3802***	−0.1443*	0.2359***	0.4346***	0.0022	0.4368***
	(6.22)	(-1.72)	(3.47)	(7.30)	(0.02)	(3.28)
E	0.1310***	0.3050***	0.4360***	0.1370***	−0.0995	−0.2366**
	(-5.47)	(-5.72)	(-7.78)	(-5.74)	(-0.90)	(-2.00)
F	0.6417***	−0.7375**	−0.0959	0.6706***	−0.6023*	0.0683
	(6.57)	(-2.37)	(-0.28)	(6.58)	(-1.81)	(0.18)
I	0.0201	0.1761***	0.1962***	0.0969***	−0.0653	0.0316
	(0.61)	(3.14)	(3.82)	(2.97)	(-0.68)	(0.31)
lnP	0.0043	0.0067	0.0110	0.0008	−0.0045	−0.0037
	(0.66)	(0.43)	(0.60)	(0.12)	(-0.12)	(-0.10)
lnN	0.0014	−0.0141**	−0.0126*	0.0127**	−0.0281**	−0.0154
	(0.25)	(-1.97)	(-1.84)	(2.46)	(-2.29)	(-1.11)
lnC	−0.0036*	0.0012	−0.0024	−0.0043**	−0.0085	−0.0127
	(-1.72)	(0.29)	(-0.57)	(-1.99)	(-1.16)	(-1.62)

Note: ① * * *, * *, * indicate significant at confidence levels of 1 %, 5 %, and 10 %, respectively; ② T values in parentheses.

Table 13
Test results of direct and indirect effects of the high-end service industry.

Variable	M7			M8		
	Direct	Indirect	Total effect	Direct	Indirect	Total effect
HSI	0.6030***	0.1490	0.7520***	0.6085***	0.4173	1.0258***
	(9.54)	(1.15)	(5.45)	(9.68)	(1.57)	(3.78)
E	0.1051***	0.2060***	0.3111***	0.1109***	−0.0371	−0.1479
	(-4.59)	(-4.02)	(-5.71)	(-4.87)	(-0.38)	(-1.40)
F	0.5965***	−0.6431**	−0.0466	0.6289***	−0.6153**	0.0135
	(6.45)	(-2.26)	(-0.15)	(6.44)	(-2.08)	(0.04)
I	−0.0066	0.2029***	0.1963***	0.0626**	−0.0185	0.0441
	(-0.21)	(3.95)	(4.23)	(2.04)	(-0.21)	(0.48)
lnP	0.0007	−0.0058	−0.0051	0.0027	−0.0208	−0.0180
	(0.11)	(-0.41)	(-0.30)	(0.44)	(-0.62)	(-0.51)
lnN	0.0061	−0.0012	0.0050	0.0185***	−0.0105	0.0080
	(1.14)	(-0.19)	(0.98)	(3.83)	(-1.18)	(0.83)
lnC	−0.0026	0.0080**	0.0053	−0.0031	0.0080	0.0049
	(-1.39)	(2.41)	(1.61)	(-1.62)	(1.63)	(0.95)

Note: ① * * *, * *, * indicate significant at confidence levels of 1 %, 5 %, and 10 %, respectively; ② T values in parentheses.

5. Conclusions and policy implications

5.1. Research conclusions

This study develops an evaluation index system for assessing industrial ecologicalization efficiency based on the dimensions of industrial input and output, and the entropy method is employed to compute the industrial ecologicalization efficiency of 30 provinces across China. Moreover, panel data spanning the period from 2007 to 2018 are selected, and the spatial Durbin model is utilized to estimate the effects of structure upgrading of the service industry on regional industrial ecologicalization efficiency, in order to explore the strategic importance and direction of service structure adjustment for industrial ecology. Finally, the research findings are outlined as follows:

First, it has been determined that industrial ecological efficiency exerts a significant positive spatial effect on the industrial ecological development of surrounding areas. Upon assessing the industrial ecological efficiency, it has been discovered that those in the east of China considerably exceeded those in other geographical parts. Concomitantly, the spatial effect results show that the improvement of local industrial ecologicalization efficiency has a positive effect on the industrial ecology of surrounding areas, which also confirms the agglomeration phenomenon of regional industrial ecological efficiency.

Second, the productive service industry plays a crucial role in enhancing industrial ecological efficiency, but has a negative spatial correlation with the efficiency of adjacent areas. Competition within the industrial economy reveals that any significant improvements in the development of productive services in neighboring regions will inevitably appeal to more labor and consumer groups, thus generating negative spatial spillover effects on the industrial economic efficiency of the local area.

Third, there is a notable positive correlation between the high-end service industry and industrial ecological efficiency, but industrial underdevelopment may weaken its spatial effects. While high-end services can contribute considerably towards enhancing local industrial ecological efficiency, their impact on nearby regions is not entirely discernible. The indirect effect between adjacent areas suggests a possible low level of agglomeration quality for high-end service industries in current regions, thereby hindering the generation of positive spatial spillover effects.

The research conclusion of this study supports the promotion effect of industrial upgrading on ecological efficiency, which is consistent with the empirical conclusions of previous studies on industrial upgrading and green development. However, the different conclusion is that the estimation results of spatial effects reflect that the lag in structural upgrading of the service industry hinders the improvement in China's industrial eco-efficiency. Specifically, the agglomeration of producer services has a "siphon effect" on the surrounding areas, resulting in enlarging the regional differences of industrial ecologization. The development of high-end service industries is backward, and it is difficult to have a positive spatial spillover effect on regional industrial ecologization.

The research limitations of this study mainly exist in two aspects: First, there are certain limitations in the evaluation of industrial ecological efficiency by the entropy value method, such as ignoring the significance of the index itself; some scholars also use analytic hierarchy processes, DEA efficiency, and other methods for evaluation, so there is room for improvement in how to more accurately estimate industrial ecologization. Second, the influencing mechanism remains to be further explored. This study does not empirically estimate the impact difference between producer services and high-end services under different upgrading modes such as industrial agglomeration and industrial convergence, but it can be further explored in future studies.

5.2. Policy implications

Based on the conclusions of this study, the following policy recommendations are proposed.

(1) Enhancing coordination and cooperation among regions and facilitating the spatially balanced development of industrial ecological efficiency. The findings of extensive research indicate that improving local industrial ecological efficiency has a constructive spatial spillover effect, resulting in positive impacts on the surrounding areas. This demonstrates the forming of resource sharing and exchange mechanisms such as technology, capital, and talent between regions, which immensely supports the creation of a favorable cooperation environment. As a result, it is highly recommended to reinforce cooperative mechanisms such as information exchange, technology transfer, and resource sharing between regions to foster regional complementary advantages and promote mutually beneficial development.
(2) Second, prevent the "congestion effect" caused by the agglomeration of producer services, and promote and regulate their orderly development. Enhance the technological innovation and talent development of producer services in underdeveloped areas, foster innovative and unicorn enterprises in the field of producer services, and enable them to offer more efficient, low-carbon, and energy-saving services for the real economy. To prevent excessive competition and pollution transfer, reinforce the industry supervision and assessment of producer services, avoid the output of high-consumption and high-emission obsolete technologies to underdeveloped areas, and mitigate the adverse spatial spillover effect of producer services on the industrial ecological efficiency of neighboring areas.
(3) Strengthening the dominant role of high-end services and promoting the high-quality development of regional industries. High-end services offer advanced technology, management experience, market insights, and other essential resources that help other industries form core competitiveness and branding advantages. To speed up the development of high-end services, we should improve their quality and level of cluster formation, eliminate institutional obstacles hindering their progress, and stimulate market potential and vitality to produce regionally unique, world-class high-end services. Furthermore, we should foster cross-regional and cross-industry partnerships to widen and deepen collaboration in high-end services, thereby boosting the coordinated and high-quality advancement of regional industries.

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Data availability statement

The data associated with the study will be made available based on the request. All data utilized in this study are sourced from public yearbook, as detailed within the text. The raw data can be downloaded from https://data.cnki.net/.

Additional information

No additional information is available for this paper.

CRediT authorship contribution statement

Chun Fu: Supervision, Resources, Project administration. **Chuanyong Luo:** Writing – review & editing, Writing – original draft. **Yezhong Liu:** Software, Data curation.

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.

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