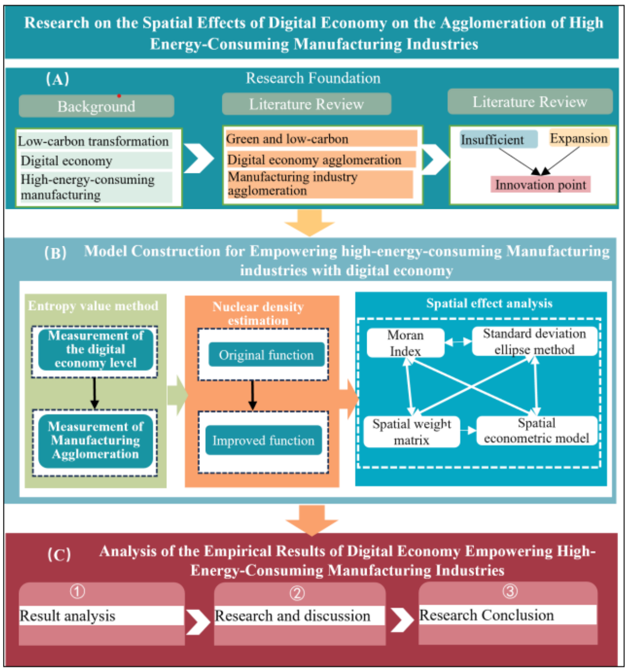
Global NEST Journal, Vol 27, No 10, 07444

Empirical Study on the Spatial Effect of High Energy Consuming Manufacturing Industry

Gang Zeng*, **Qichen Li, Sana Wuren, Ying Zhang, Yue Zhang, Yahong Zhang, Huimin Chen, MinCao, Qiunan Chen and Han Wang**
School of economics and management, Civil Aviation University of China, Tianjin 300300, China
Received: 11/03/2025, Accepted: 04/10/2025, Available online: 22/10/2025
*to whom all correspondence should be addressed: e-mail: gzeng@Cauc.edu.cn
https://doi.org/10.30955/gnj.07444

Graphical abstract



Abstract

The carbon emissions and high energy consumption of high energy-consuming manufacturing industries pose a huge threat to the environment. Promoting the green transformation of high energy-consuming manufacturing industries has become an important research topic. The vigorous development of the digital economy has provided a brand-new impetus for the green upgrading of high-energy-consuming manufacturing industries. Based mainly on the data of 31 provinces in China from 2012 to 2022, this article measures the level of the digital economy by applying the entropy weight method and assesses the agglomeration index of high energy-consuming manufacturing industries by using location entropy. Then, a spatial econometric model is constructed to analyze the spatial effect of the digital economy on the agglomeration of high energy-consuming manufacturing industries. Through theoretical and empirical analysis, the following research conclusions are drawn: ① The development of the digital economy in different provinces of China shows significant heterogeneity. The digital economy in the central region has developed rapidly, while that in the eastern region is at a relatively high level. There are significant differences between the two regions. ② There is regional heterogeneity and complexity in the agglomeration development of high energy-consuming manufacturing industries. Taking the Beijing-Tianjin-Hebei region as a typical example for analysis, the agglomeration level of high energy-consuming manufacturing industries in Tianjin City, Tangshan City and Langfang City has increased significantly, but the overall agglomeration level shows a dispersed trend. The development of the digital economy has effectively promoted the agglomeration of high energy-consuming manufacturing industries. The influence coefficients of the digital economy on the agglomeration of high energy-consuming manufacturing industries are 0.863 and 0.670 respectively, which are significantly positive. ④ The digital economy has a positive spatial spillover effect on the agglomeration level of high energy-consuming manufacturing industries. According to the results of empirical tests, the development of the digital economy plays a role in promoting the improvement of the agglomeration level of high energy-consuming manufacturing industries. Finally, based on the research results, the study put forward relevant suggestions such as strengthening the construction of digital infrastructure, increasing investment in the digital industry in the western region, and enhancing the spatial agglomeration of high energy-consuming manufacturing industries to reduce industrial costs.

Keyword: Green transformation；High energy-consuming manufacturing industry；Digital economy；Entropy weight method；Spatial spillover effect

1. Introduction

Promoting the development of China's industrial economy towards green, high-end, and energy-efficient industries is an important direction. Currently, China's traditional manufacturing industry still dominates, and environmental problems caused by high energy consumption and pollution continue to pose enormous challenges to China's economic development. Vigorously promoting energy conservation, emission reduction, and green transformation in high energy consuming manufacturing industries is an important trend for sustainable development.

Thanks to the rapid development of communication technology, China's digital economy has achieved significant success, providing new impetus for the green transformation of high energy consuming manufacturing industries. In recent years, with the further breakthrough and wide application of new generation information technologies such as the Internet, big data, cloud computing, artificial intelligence, and the deep integration of digital knowledge and information with the real economy, human society has entered the digital economy era (Du *et al.* 2023). The "Report on the Development of China's Urban Digital Economy (2023)" shows that the current scale of China's digital economy exceeds 50 trillion Yuan, ranking second in the world in terms of total volume, and accounting for 41.5% of GDP. The integration of the digital economy and the real economy is becoming increasingly close. The manufacturing industry is the core of the real economy and the key to high-quality development of the national economy. Among them, high energy consuming industries are an important component of the national economy. According to data from the National Bureau of Statistics, the total energy consumption of the six high energy consuming industries (thermal power, steel, non-metallic mineral products, refining and coking, chemical industry, and non-ferrous metals) accounts for more than 50% of China's total energy consumption, and the proportion of carbon dioxide emissions is close to 80%. Therefore, in-depth research is needed on the spatial effects of provincial digital economy on the agglomeration of high energy consuming manufacturing industry and the spatial pattern evolution of high energy consuming industries, it is of great practical significance for the high-quality development of the digital economy and high energy consuming manufacturing industry. At present, research on the agglomeration of digital economy and manufacturing industry can be summarized into the following two points:

1 Number 1: Empowering the manufacturing industry with green and low-carbon development and transformation and upgrading. The development of the digital economy can reduce carbon emissions (Fan *et al.* 2023; Guo *et al.* 2022,2024; He *et al.* 2016), and improving the level of digitization can promote the green transformation of manufacturing enterprises through three influencing mechanisms: innovation capability, structural optimization, and resource utilization. In terms of innovation factors (Li *et al.* 2024; Liao *et al.* 2021, 2024; Liu *et al.* 2023), the digital economy has a positive impact on the innovation efficiency of the manufacturing industry and has spatial spillover characteristics. Starting from four different dimensions: infrastructure, digital industrialization, industrial digitization, and digital governance, this study investigates the dual effects of the digital economy on technological innovation in the manufacturing industry. For high energy consuming manufacturing industries, some scholars have proposed the Industrial SGVAR model to find ways for the rapid growth of high energy consuming industries (Liu *et al.* 2023, 2024; Ma *et al.* 2022), and have estimated the environmental total factor productivity of China's high energy consuming industries (Pan *et al.* 2022; Qi *et al.* 2020; Shen *et al.* 2011; Wang *et al.* 2023).

2 Number 1, the economy affects the agglomeration of manufacturing industry by 1 level. In terms of regional development, the overall level of high-quality coordinated development of digital economy and manufacturing industry in various regions is on the rise, and regional differences are gradually decreasing (Wang *et al.* 2024a, 2024b; Wu *et al.* 2018). At the same time, the environmental effects of digitalization in manufacturing also exhibit significant industry and regional heterogeneity. In terms of industry heterogeneity, the agglomeration of high-tech manufacturing can significantly improve local green innovation efficiency (Yang *et al.* 2023; Ye *et al.* 2019). At the national scale, there is a "U-shaped" relationship between manufacturing agglomeration and green utilization efficiency of industrial land (Zeng *et al.* 2019).

Green innovation in industries is particularly important for enhancing the performance level of carbon reduction. Digital transformation can increase the contribution of green innovation to the carbon reduction performance of high energy-consuming enterprises. Against the backdrop of promoting carbon reduction in the manufacturing industry, it is of great significance to study the impact path of the digital economy on high energy-consuming manufacturing industries. Based on the above literature review, it can be known that there are currently abundant achievements related to the digital economy, manufacturing development, and low-carbon transformation, and many scholars have formed a large number of scientific achievements. However, relatively few scholars have conducted systematic and in-depth research on the relationship between the digital economy and high-energy-consuming manufacturing industries.

Therefore, this paper will further expand on the existing research and strive to make valuable discoveries. The possible innovations of this article are manifested as follows: First, the paper constructs a theoretical framework for the impact of the digital economy on high-energy-consuming manufacturing industries. Incorporating the relationship between the development of the digital economy and high-energy-consuming manufacturing industries into a unified system for consideration effectively takes into account the issues of industrial development and green transformation. Second, introduce and modify multiple models to construct an entropy weight method model for the development level of the digital economy, a kernel density estimation model considering the characteristics of the digital economy, and a spatial effect model analyzing the relationship between the digital economy and high-energy-consuming manufacturing industries. By adopting multiple mathematical models, problems can be scientifically and accurately identified. Thirdly, conduct empirical analysis and research on the problem using multi-source data, and propose targeted strategies that are conducive to promoting energy conservation and emission reduction in high energy-consuming manufacturing industries. The research of this paper is of practical significance for promoting the high-quality and coordinated development of the digital economy, facilitating the transformation and upgrading of China's industrial manufactured goods, and enhancing the high-quality development of high-energy-consuming manufacturing industries (the technical route of the research is shown in **Figure 1**).

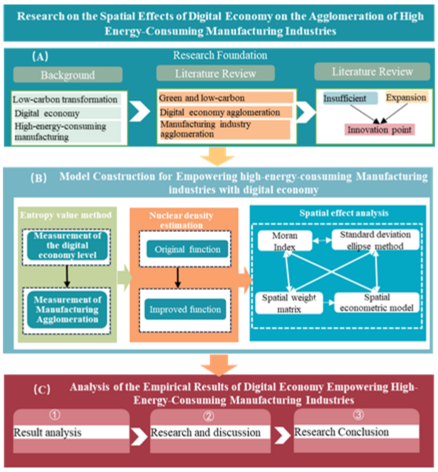


Figure 1. The technical roadmap of the thesis research

2. Material and Methods

2.1. *Entropy Weight Model - Digital Economy Measurement*

This article uses the entropy weight method, which is commonly used in existing research to measure the digital economy (Zhao *et al.* 2024), to construct a comprehensive evaluation index system from four dimensions: digital industrialization, industrial digitization, digital economic development carriers, and digital economic environment, in order to evaluate the development level of the digital economy (**Table 1**). The entropy weight method is based on the concept of information entropy, which is an indicator of the degree of information concentration. It represents the maximum amount of information in a random variable when the sum of the probabilities of each value appearing is 1. The smaller the information entropy, the more concentrated the information, and vice versa, the more dispersed the information. The entropy weight method calculates the information entropy of each indicator to determine the weight of each indicator, thereby achieving multi-indicator decision-making. The specific implementation formula is as follows:

(1) Indicator Description: The research year span is d, the number of evaluation indicators is m, and n is the number of provinces, $x_{\theta ij}$ representing the i of the j indicator of the province in the year.

(2) Standardization of indicators:

$$x'_{\theta ij}=\frac{x_{\theta ij}-x_{\theta j}^{\min}}{x_{\theta j}^{\max}-x_{\theta j}^{\min}},i=1,2,\cdots,n;j=1,2,\cdots,m \tag{1}$$

$$x'_{\theta ij}=\frac{x_{\theta j}^{\max}-x_{\theta ij}}{x_{\theta j}^{\max}-x_{\theta j}^{\min}},i=1,2,\cdots,n;j=1,2,\cdots,m \tag{2}$$

Among them, $x_{\theta j}^{\min}$ and $x_{\theta j}^{\max}$ are the minimum and maximum values of the indicators, respectively;

(3) Quantify the data:

$$y_{\theta ij}=\frac{x'_{\theta ij}}{\sum_{\theta=1}^{r}\sum_{i=1}^{n}x'_{\theta ij}} \tag{3}$$

(4) Determine the weight of each indicator:

$$e_j=-k\sum_{\theta=1}^{r}\sum_{i=1}^{n}y_{\theta ij}\times\ln y_{\theta ij} \tag{4}$$

Among them, $k>0$, $k=-\frac{1}{\ln(rn)}$, $e_j\geq 0$.

The coefficient of difference for the j indicator is: $g_j=1-e_j$;

The weight of the j indicator is:

$$\omega_j=\frac{g_j}{\sum_{j=1}^{m}g_j} \tag{6}$$

(5) Calculate the comprehensive development index:

$$U_i=\sum_{j}^{m}\omega_j x'_{\theta ij} \tag{7}$$

Among them, x'_{ij} is the standard value of each indicator in the indicator system, ω_j is the weight assigned to each indicator through the entropy weight method, where, the U larger the value, the better the sample effect used, and also indicates the higher level of digital economic development in the province.

2.2. *Location Entropy Model-Measurement of High Energy Consumption Manufacturing Agglomeration*

One of the commonly used methods for measuring agglomeration level is location entropy. Considering that it is difficult to obtain data on various aspects of high energy consuming manufacturing industries, this article calculates the location quotient based on the number of employed people at the provincial level. The total number of employed people in manufacturing, mining, and supply industries such as electricity and heat defined as the number of employed people in high energy consuming manufacturing industries; In terms of city level data, the location quotient is calculated through gross domestic product, and the specific formula is as follows:

$$Hag_{it}=\frac{X_{it}/\sum_i X_{it}}{D_{it}/\sum_i D_{it}} \tag{8}$$

In the formula, Hag_{it} represents the agglomeration level of high energy consuming manufacturing industry, and X_{it} represents the number of high energy consuming industries in the t_{year} of the i province (or the gross domestic product of the second industry in the t_{year} of the *I* prefecture level city); D_{it} Indicate the total number of employed people in the entire industry in the t_{year} of the *i* province (or the gross domestic product of the prefecture level city in the year); $\sum_i X_{it}$ Indicate the total number of employed people in high energy consuming industries in all provinces (or the sum of the annual gross domestic product of the secondary industry in the Beijing-Tianjin-Hebei region); $\sum_i D_{it}$ Indicate the number of employed people in all provinces and industries (or the sum of the t_{year} regional GDP of the Beijing-Tianjin-Hebei region)

2.3. *Kernel Density Estimation Model*

Kernel density estimation is a nonparametric testing method used in probability theory to estimate unknown density functions. It was proposed by Rosenblatt (1955) and Emanuel Parson (1962) and is also known as the Parson window. The key idea of kernel density estimation is to obtain a reasonable and estimated density function through kernel density estimation [Zhong *et al.* 2024]. The formula for estimating the kernel density function is as follows:

$$f(x)=\frac{1}{nh}\sum_{i=1}^{n}K(\frac{X_i-x}{h})=\frac{1}{n}\sum_{i=1}^{n}K(X_i-x) \tag{8}$$

Among them, $K(\cdot)$ is the kernel function, essentially a weight function, and $K_h(x)=K(x/h)/h$; the h larger the h window width, the x higher the probability of it appearing in nearby fields, and the $f(x)$ smoother the estimated density function.

There are various forms of kernel functions for kernel density estimation, such as Gaussian kernel, Epanechnikov kernel, Weight kernel, etc. This article uses Gaussian kernel function and Epanechnikov kernel function to analyze the development level of digital economy and high energy consumption agglomeration. The forms of Gaussian function and Epanechnikov kernel function are as follows:

$$K(x,x')=\frac{1}{\sqrt{2\pi}\sigma}\exp\left(-\frac{(x-x')^2}{2\sigma^2}\right) \tag{9}$$

Among them, x,x' is the sample value and σ is the free parameter.

$$K(x)=\frac{3}{4}(1-x^2)I,(|x|\le 1) \tag{10}$$

Among them, it $I(\cdot)$ is an indicative 0-1 function, with a $I(\cdot)$ $I(\cdot)$ value of 1 $|x|\le 1$ when it holds and 0 $|x|\le 1$ when it does not hold.

2.4. *Research Methods for Spatial Effects*

2.4.1. Moran's Index

The Moran index is mainly used to measure whether there is spatial clustering in spatial data. This article uses Moran's index to test whether there is spatial autocorrelation in the agglomeration level of high energy consuming manufacturing industries in different provinces. The Moran's I index value range is (-1,1). When the Moran's I index is positive, it indicates the existence of spatial positive autocorrelation, and when the index is negative, it indicates the existence of negative spatial autocorrelation. The specific calculation formula is as follows (Zhou *et al.* 2023):

$$Moran'I=\sum_{i=1}^{N}\sum_{j=1}^{N}w_{ij}(h_i-\bar{h})(h_j-\bar{h})\Big/\sum_{i=1}^{N}\sum_{j=1}^{N}w_{ij}\sum_{i=1}^{N}(h_j-\bar{h})^2 \tag{12}$$

In the formula, w_{ij} is the spatial weight matrix, h_i,h_j is the agglomeration level of high energy consuming manufacturing industries in each province, and N is the total provincial score.

2.4.2. Analysis of Spatial Evolution Characteristics

The centroid standard deviation ellipse algorithm is a commonly used method in spatial statistics research, first developed by sociology professor Welty at the University of Southern California in the United States D. Welty Lefebvre proposed in 1926 that this method is used to explore the spatial distribution evolution process of high energy consuming manufacturing agglomeration in the Beijing-Tianjin-Hebei region. The main parameter calculation formulas are as follows:

Determine the center of the circle:

$$SDE_x=\sqrt{\sum_{i=1}^{n}(x_i-\overline{X})^2/n} \tag{12}$$

$$SDE_y=\sqrt{\sum_{i=1}^{n}(y_i-\overline{Y})^2/n} \tag{13}$$

Elliptical azimuth angle:

$$\tan\theta=\frac{(\sum_{i=1}^{n}x_i^{\ 2}-\sum_{i=1}^{n}y_i^{\ 2})+\sqrt{(\sum_{i=1}^{n}x_i^{\ 2}-\sum_{i=1}^{n}y_i^{\ 2})^2+4(\sum_{i=1}^{n}x_iy_i)^2}}{2\sum_{i=1}^{n}x_iy_i} \tag{14}$$

Length of X-axis and Y-axis:

$$\sigma_x=\sqrt{2}\times\sqrt{\frac{\sum_{i=1}^{n}(x_i\cos\theta-y_i\sin\theta)^2}{n}} \tag{15}$$

$$\sigma_y=\sqrt{2}\times\sqrt{\frac{\sum_{i=1}^{n}(x_i\sin\theta+y_i\cos\theta)^2}{n}} \tag{16}$$

Among them y_i , x_i sum y_i is the spatial coordinate of the element, $\overline{X}$ sum $\overline{Y}$ is the arithmetic mean center coordinate, sum is the difference between the element and the mean center coordinate, x_i and θ is the azimuth angle rotated clockwise with the due north direction as the reference

2.4.3. Spatial Weight Matrix

A spatial weight matrix is a matrix used to describe spatial proximity or spatial relationships. After multiple verifications and selections, this article chooses the inverse distance square matrix and the economic distance matrix as spatial weight matrices Moran. The economic distance matrix is used as the spatial weight matrix for spatial model estimation, and the inverse distance square matrix is used as the spatial weight matrix for Moran's index test

$$W_{ij}^{1}=\frac{1}{\left|Y_i-Y_j\right|}, i\neq j \quad (17)$$

$$W_{ij}^{2}=\begin{cases}0, i=j\\ \frac{1}{d_{ij}^{2}}, i\neq j\end{cases} \quad (1)$$

In the formula, W_{ij}^{1} is the economic distance weight matrix, which $\left|Y_i-Y_j\right|$ is the j difference between the per capita GDP of the i province;

W_{ij}^{2} is the inverse distance squared space weight matrix, d_{ij} is the distance between provincial capitals.

2.4.4. Spatial econometric model

This article constructs the following model based on the research of Cheng Junkie et al. and spatial econometric theory:

$$y_{it}=\rho\times W_{ij}\times y_{it}+\sum_{i=1}^{n}W_{ij}\times X_{ijt}\times\theta+\alpha X_{ijt}+\mu_i+\delta_t+\varepsilon_{it} \quad (19)$$

$$\varepsilon_{it}=\lambda\times W_{ij}\times\varepsilon_t+\nu_{it} \quad (20)$$

Among them, Y_{it} is the dependent variable, representing the concentration level of high energy consuming manufacturing industry in the province, $\rho\times W_{ij}\times y_{it}$ is the spatial lag term of Y_{it}, W_{ij} is the spatial weight matrix; X_{ijt} is the core explanatory variable, representing the development level of digital economy, $\sum_{i=1}^{n}W_{ij}\times X_{ijt}\times\theta$ is its spatial lag term; μ_i represents spatial effect, δ_t represents time effect; ε_{it} is the spatial error of the disturbance term; λ is the spatial error coefficient of the disturbance term; $\varepsilon_t\sim(0, \sigma^2)$. Common spatial econometric models include: spatial hysteresis Model (SAR), Spatial Error Model (SEM), and Spatial Durbin Model (SDM). This paper will select different spatial econometric models based on the values of λ, θ and ρ.

The selection criteria can draw on the ideas of some scholars. Firstly, OLS regression is conducted to determine whether it has spatial error effects and spatial lag effects through LM test. If both are present, the spatial regression model is selected, which is a pre-test. Post hoc testing is divided into three steps. The first step is to use the Housman test to determine whether the spatial regression model is suitable for fixed effects or random effects. Then, the likelihood ratio (LR) test is performed. Assuming the use of a spatial Durbin model, pairwise comparisons are made to determine whether the spatial Durbin model has degraded to a spatial error model or a spatial lag model. Finally, the Wald test is used to determine whether the spatial Durbin model has degraded to a spatial error model or a spatial lag model. Finally, the appropriate type of spatial measurement model for the data sample in this article is determined by comparing the test results.

Table 1. Comprehensive Evaluation Index System for the Development Level of Digital Economy in Provinces

First level indicator	Secondary indicators	Company
Industrial digitalization	Proportion of Enterprise E-commerce to GDP	%
	Number of websites per hundred enterprises	individual
	Number of computers used per 100 people in enterprises	individual
	Proportion of enterprises engaged in e-commerce transactions	%
	Digital Inclusive Finance Index	—
	Proportion of information technology service revenue to GDP	%
Digital Industrialization	Proportion of total telecommunications business to GDP	%
	Proportion of software business revenue to GDP	%
	Number of employees in the information service industry	ten thousand people
Carrier of Digital Economy Development	Number of Internet broadband access ports	Ten thousand
	Number of Internet broadband access users	Ten thousand households
	Number of Domain Names	Ten thousand
	Mobile phone penetration rate	Department/100 people
	Length of long-distance optical cable per unit area	rice
Digital Economy Environment	Total transaction amount of technical contract	Ten thousand yuan
	Number of patent applications authorized	piece
	Number of R&D projects (projects) for industrial enterprises above a certain scale	term
	R&D expenditure of industrial enterprises above designated size (RMB 10000)	Ten thousand yuan
	Equivalent full-time equivalent (person year) of R&D personnel in industrial enterprises above designated size	Person/year

2.5. *Sample selection and data sources*

Regarding the level of the digital economy, the spatial agglomeration of high-energy-consuming manufacturing industries, and the spatial spillover effects of the digital economy on high-energy-consuming manufacturing industries, the main data is sourced from the "China Statistical Yearbook 2013-2023". Due to the lag of statistical yearbooks, the current year's statistical yearbook mainly discloses the data of the previous year, and some environmental data are also obtained from the public data of the National Bureau of Statistics. In addition, during the research process, considering the spatial agglomeration characteristics of high energy-consuming manufacturing industries, data from the Beijing-Tianjin-Hebei region was selected as a typical case for analysis. The relevant data were sourced from local statistical yearbooks of Beijing, Tianjin and Hebei. In addition, due to the absence of some data, the linear difference method is used to complete it.

2.6. *Variable Description*

The development of the digital economy can be measured through multiple dimensions. According to Zhou Quran's research, the digital economy can be divided into four aspects: industrial digitization, digital industrialization, digital economy development carrier, and digital economy environment. 19 secondary indicators are selected for comprehensive evaluation (**Table 1**)

After multiple tests and selections, five variables including regional GDP, foreign direct investment, market size, fiscal expenditure, and transportation were ultimately selected as control variables. The specific descriptions are as follows:

1. Regional Gross Domestic Product (GDP): Use the logarithm of GDP to measure.

2. Market scale: measured by taking the logarithm of the number of units in industrial enterprises above a certain scale

3. Foreign investment (fdi): measured by taking the logarithm of the proportion of foreign investment to per capita GDP

4. Fiscal expenditure (Fe): measured by taking the logarithm of local general fiscal expenditure

5. Transportation (Tran): measured by taking the logarithm of the number of railway and highway employees

3. Results and Discussion

3.1. *Analysis of the Development Level of Digital Economy in Different Regions*

Using formula (8) and MATLAB to draw a three-dimensional dynamic Kernal kernel density map of the development of digital economy in Chinese provinces, in order to better demonstrate the characteristics of the trend of digital economy development level, as **Figure 2** follows:

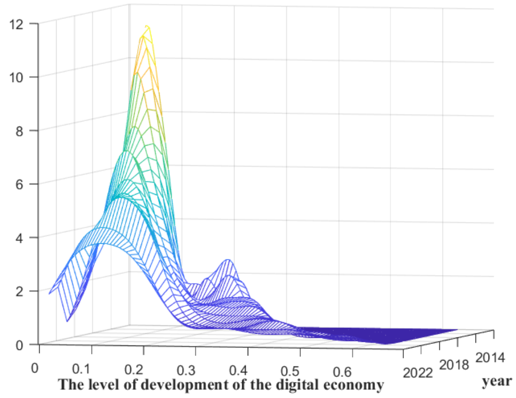


Figure 2. 3D Core Density Map of Digital Economy Development in Provinces

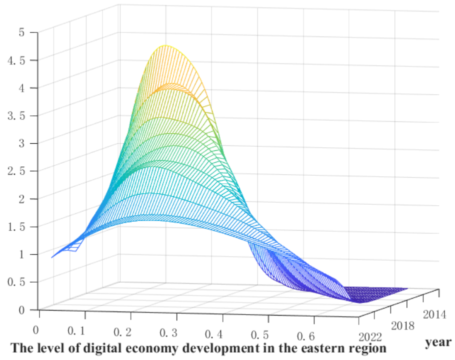


Figure 3. 3D Core Density Map of Digital Economy Development in the Eastern Region

After observation, it is not difficult to see that during the research period, the digital economy center of gravity in various provinces of China continued to shift to the right, indicating that the level of digital economy development in each province is constantly improving; The distribution of China's URBAN digital economy from 2012 to 2014 showed a bimodal and steep pattern, with small differences between provinces. After 2014, the peak gradually decreased, while the distance between peaks gradually increased. This indicates that since 2012, the digital economy has shown a multipolar development trend, and the development gap is constantly widening; The peak values are mostly concentrated around 0.1, indicating that the large sample group of digital economy development levels in Chinese provinces is mainly concentrated around 0.1.

From **Figure 3**, it can be seen that during the research period, the fluctuation center of the kernel density function continued to shift to the right, indicating an overall upward trend in the development level of the digital economy in the eastern region. From a distribution perspective, the peak of the digital economy in the eastern region has been declining since 2012, indicating a gradual decrease in differentiation; Compared with the national average, the peak value of digital economy development in eastern provinces is ~between 0.20.3, which is higher than the overall range of 0.1-0.2 for the digital economy. This indicates that the digital economy development in eastern provinces is higher than the national average.

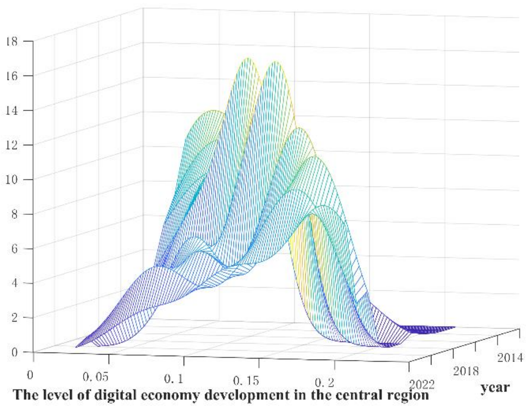


Figure 4. Dimensional kernel density map of digital economy development in the central region of China

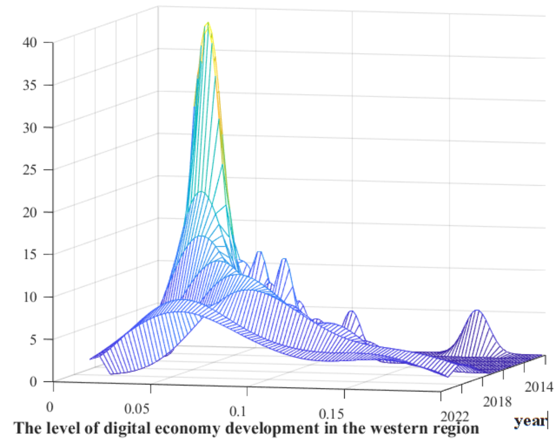


Figure 5. 3D Core Density Map of Digital Economy Development in Western Regions

From **Figure 4**, it can be seen that the fluctuation center of the kernel density function during the sample period shifts to the right, and the amplitude of the shift is significant, indicating that the overall development level of the digital economy in the central region is rapidly improving. From the analysis of distribution patterns, there were two distinct peaks between 2014 and 2020, indicating a significant difference in the level of digital economy development in the central region. From the extension characteristics of the distribution, the kernel density curve of the level of digital economy development has shifted from a "left tail" to a "right tail". In terms of the number of peaks, there is a clear bimodal distribution from 2018 to 2022, indicating a multipolar trend in the development of the digital economy in the central region.

From **Figure 5**, it can be seen that the fluctuation center of the kernel density curve continues to move to the right, indicating an overall improvement in the development of the digital economy in the western region. At the same time, after 2014, the height of the main peak of the kernel density function significantly decreased, indicating a significant reduction in the degree of differentiation in the development of the digital economy in the western region. This may be due to the implementation of the Western Development Strategy and the government's increased attention to the development of the western region; The core density curve of the development level of digital economy in western provinces also shows a "right tail" characteristic similar to that of the whole country and eastern regions.

3.2. *Analysis of the Development Level of High Energy Consumption Manufacturing Agglomeration in Different Regions*

In order to visually demonstrate the agglomeration level, distribution evolution, peak value, extensibility, and polarization trend of high energy consuming manufacturing industries in provinces, a two-dimensional Kernel density combination chart of digital economy development in Chinese provinces is drawn using formula (9) and STATA, as **Figure 6** follows:

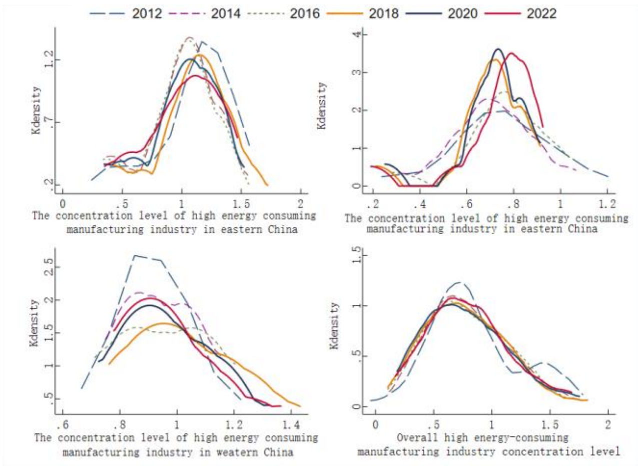


Figure 6. Map of High Energy Consumption Agglomeration Core Density in Different Regions

For the western region, from 2012 to 2022, the overall nuclear density curve shifted to the right, indicating that the agglomeration level of high energy consuming manufacturing industries in the western region gradually improved. The peak of the curve from 2012 to 2026 was projected around 0.65 on the x-axis, while from 2016 to 2022, the peak projection of the curve shifted to around 0.8 and increased, further indicating the improvement of the agglomeration level of high energy consuming industries in the western region and the rapid growth rate in recent years

3.3. *Analysis of Spatiotemporal Characteristics of High Energy Consumption Manufacturing Agglomeration*

Using ARIGIS software to create a spatiotemporal evolution trend map of high energy consuming manufacturing agglomeration in various provinces of China, as shown in **Figure 7**, **Figure 7** Spatiotemporal Evolution Trend of High Energy Consumption Manufacturing Agglomeration in Various Provinces of China

Note: Based on the standard map with approval number GS (2024) 0625, the boundary of the base map has not been modified

From 2012 to 2022, the agglomeration level of high energy consuming manufacturing industries in the eastern region is at a medium to high level, with higher agglomeration levels in the eastern coastal areas, mainly in provinces such as Jiangsu, Zhejiang, Fujian, and Guangdong; The level of high energy consuming manufacturing agglomeration in the central region has steadily improved, with provinces such as Hubei and Anhui shifting from "yellow" to "orange", and high energy consuming agglomeration rising in Chengdu; The low level of agglomeration is the Xizang Autonomous Region and Xinjiang Uygur Autonomous Region, while the agglomeration degree of high energy consuming manufacturing industry in Heilongjiang Province and Gansu Province is relatively declining. In general, the high energy consuming agglomeration shows a polarization trend. The agglomeration degree in the eastern region increases while that in the western region and some provinces decreases

3.4. *Evolution of spatial pattern*

From 2012 to 2022, the high energy consuming manufacturing agglomeration center in the Beijing-Tianjin-Hebei region shifted from Baoding City to Lang fang City (**Table 2, Table 3, Figure 8**), with a total transfer distance of 16.42km. Among them, the longest transfer distance was 7.13km from 2017 to 2019, showing an overall southeast direction transfer trajectory. This indicates that the high energy consuming manufacturing agglomeration in the southeastern region of the Beijing-Tianjin-Hebei region is gradually increasing, and the elliptical area fluctuates within the research scope. The circumference shows an increasing trend, and the difference between the long and short axes has been increasing year by year since 2015, indicating that the directionality of high energy consuming manufacturing agglomeration in the Beijing Tianjin Hebei region has been strengthened. The long half axis of the ellipse has increased from 2.51 in 2013 to 2.60 in 2022, and the increase is relatively small. The spatial distribution of manufacturing agglomeration is becoming increasingly dispersed in the main direction, namely the northeast southwest direction, but the degree of dispersion is not significant.

Table 2. Transfer of High Energy Consumption Manufacturing Agglomeration Centers in the Beijing-Tianjin-Hebei Region

Year /Year	2013-2015	2015-2017	2017-2019	2019-2022
Center displacement distance/km	1.87	4.53	7.13	2.89

Table 3. Elliptical Parameters of Standard Deviation of High Energy Consumption Manufacturing Agglomeration in the Beijing-Tianjin-Hebei Region from 2012 to 2022 (in radians)

Year	Perimeter	The measure of area	X coordinate	Y coordinate	XStdDist	YStdDist	Rotation
2013	12.21	10.01	116.27	38.95	2.51	1.27	47.67
2015	12.25	10.14	116.29	38.97	2.52	1.28	48.00
2017	12.26	10.04	116.28	38.92	2.53	1.26	48.26
2019	12.45	10.22	116.35	38.93	2.59	1.25	48.92
2022	12.41	10.02	116.38	38.92	2.60	1.23	49.56

Table 4. Global Moran Index Test Results for High Energy Consumption Industry Agglomeration

Year	I	sd(I)	z	p-value*
H2012	0.670	0.399	1.762	0.039
H2013	1.052	0.394	2.754	0.003
H2014	0.938	0.394	2.464	0.007
H2015	0.890	0.395	2.340	0.010
H2016	0.883	0.395	2.318	0.010
H2017	1.096	0.394	2.867	0.002
H2018	1.205	0.393	3.152	0.001
H2019	1.556	0.394	4.037	0.000
H2020	1.640	0.396	4.229	0.000
H2021	1.727	0.395	4.461	0.000
H2022	1.612	0.396	4.154	0.000

3.5. *Spatial correlation test*

Using the Moran's index formula (10) to test whether there is spatial dependence in the agglomeration of high energy consuming manufacturing industries, the global Moran's index test results are shown in **Table 4**. It can be seen that from 2012 to 2022, the global Moran's index was positive and significant to varying degrees, indicating that there is a positive spatial dependence in the agglomeration of high energy consuming manufacturing industries among different provinces

From the results of the Moran’s I index, it can be seen that the agglomeration of high energy consuming manufacturing industries in 31 provinces of China from 2013 to 2022 has passed the 1% significance test and is all greater than 0, indicating a significant spatial positive correlation between the agglomeration levels of high energy consuming manufacturing industries in each province, that is, there is a significant spatial spillover effect between carbon dioxide emissions, and the overall Moran’s I index shows an increasing trend year by year, indicating that spatial dependence is gradually increasing.

To further identify the clustering situation in specific regions, scatter plots of the local Moran's index for high energy consuming manufacturing clusters in 2012, 2016, 2020, and 2022 were drawn, as shown in **Figure 9**, which all passed the 5% significance test

From the above analysis, it can be seen that the agglomeration of high energy consuming industries in provinces has spatial correlation. Therefore, a spatial weight matrix is introduced, and a spatial econometric model is used for estimation.

3.6. *Spatial effect analysis*

Table 5 presents the results of OLS regression and LM test. The results show that LM-LEG and LM-ERR are significant, indicating the existence of spatial error effect and spatial lag effect. A mixed model is not used for analysis, and the spatial Durbin model is initially selected. Subsequently, the Hausman test, LR test and Wald test were respectively used to determine whether to adopt the fixed effects model and whether the initially selected spatial Durbin model could be degraded into the SAR model and SEM model. According to the results in **Table 6**, the Hausman test results are significant. Therefore, the null hypothesis that all models are consistent is rejected, and a better fixed-effect model is adopted. The results of both the LR test and the Wald test are significant at the 1% level. Therefore, this paper selects the SDM model as the final spatial econometric model.

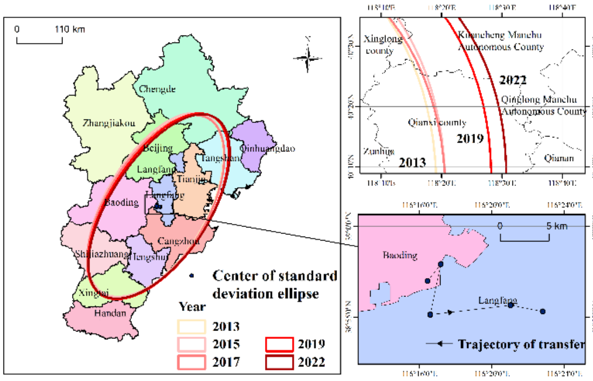


Figure 8. Evolution of spatial pattern of high energy consuming manufacturing agglomeration in the Beijing-Tianjin-Hebei region from 2012 to 2022

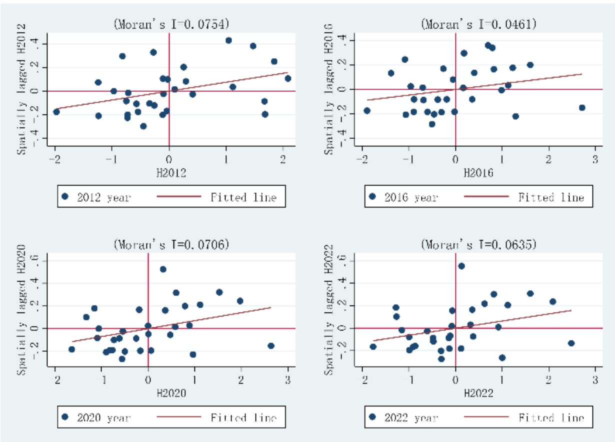


Figure 9. Local Moran scatter plot

Table 5. Estimates of non-spatial panel data and LM test estimates

Variable	Regression coefficient	p value
Dec	0.8033092***	0.000
fdi	-0.2349035***	0.000
gdp	-0.3730331***	0.000
tran	-0.029796**	0.023
scale	0.3541044***	0.000
fe	-0.0474247**	0.028
LM test no spatial error	8.713***	0.003
Robust LM test no spatial error	5.587**	0.018
LM test no spatial lag	3.147*	0.076
Robust LM test no spatial lag	0.022	0.833

Table 6. Results of Hausman test, Wald Test and LR Test

Inspection method	Statistical value	p value
LR Lag	43.96***	0.0000
LR Err	20.00***	0.0028
Wald Lag	27.99***	0.0001
Wald Err	29.05***	0.0001
Hausman	25.83***	0.0005

Table 7 shows the estimation results of the panel model. The spatial autocorrelation coefficient under the time fixed effect is -0.390. Through the significance test at the 1% confidence level, it indicates that there is a spatial spillover effect, that is, the agglomeration of high energy-consuming industries in a certain province will affect the agglomeration of high energy-consuming manufacturing industries in the surrounding areas. Specifically, the agglomeration development of high energy-consuming industries in this province will cause the agglomeration of high energy-consuming industries in the surrounding provinces to be affected Flat reduction. The possible reason is based on the fact that resource endowments vary from place to place. High energy-consuming industries have a strong dependence on resources. With the development and utilization of resources, high energy-consuming industries will shift to regions rich in resources. The agglomeration trend of high energy-consuming industries in resource-rich regions will strengthen, while the agglomeration level of high energy-consuming industries in other regions not rich in resources will weaken (Wu Chuanqing et al., 2018). Between adjacent provinces and cities, high energy-consuming industries tend to shift to regions rich in resources, which well explains the trend of high energy-consuming industries in the east moving to the west and further verifies that there is obvious spatial dependence and spatial spillover effect in the agglomeration of high energy-consuming manufacturing industries. The estimation results of the core explanatory variable Dec (digital economy development level) in the four models of this paper are 0.803, 0.670, and -0.148 respectively. The positive coefficient passes the significance test of 1%, while the negative coefficient fails. The results under the double fixed effect are not considered as they fail the significance test. This indicates a significant positive correlation between the development level of the digital economy and the agglomeration level of high-energy-consuming manufacturing industries, further confirming the validity of Hypothesis 1.

From the perspective of control variables, the influence coefficients of regional gross domestic product (gdp) on the agglomeration of high energy-consuming manufacturing industries are all negative, and the three coefficients pass the significance test of 1%. The influence coefficients of market size (scale) and transportation (tran) on the agglomeration of high energy-consuming manufacturing industries are significantly positive, indicating that an increase in market size and convenient transportation are conducive to the agglomeration of high energy-consuming industries. One possible reason is that regions with large market scales usually have more abundant resources and more complete transportation infrastructure, which are crucial for the development of high energy-consuming industries. A well-developed transportation network is more conducive to the transportation of resources and labor. That is, enterprises in high energy-consuming industries tend to gather in areas rich in resources and with convenient transportation to obtain more resources and more convenient transportation conditions. The influence coefficient of fiscal expenditure (fe) on the agglomeration of high energy-consuming industries is negative, and it passes the significance test of 5%. The possible reason is that the implementation of environmental protection and low-carbon related policies in recent years has suppressed the government's capital investment in high energy-consuming industries, and the government has focused on energy conservation and emission reduction in high energy-consuming industries. The impact coefficient of foreign investment (fdi) on the agglomeration of high energy-consuming manufacturing industries is significantly negative. The possible reason lies in the nature of the industries. Foreign investors usually possess advanced technologies and management experience. They are more inclined to invest in high value-added and high-tech industries rather than simply high energy-consuming industries. Therefore, they place greater emphasis on the importance of digitalization in high energy-consuming industries

Table 7. Estimation Results of the Panel Model

	OLS	Fixed time	Individual fixation	Double fixed
Dec	0.803***	0.670***	-0.148*	-0.0688
	(0.154)	(0.153)	(0.108)	(0.107)
fdi	-0.235***	-0.194***	-0.0191	0.0184
	(0.0498)	(0.0517)	(0.0338)	(0.0390)
fe	-0.0474**	-0.0451**	-0.00503	-0.00865
	(0.0214)	(0.0211)	(0.0141)	(0.0139)
gdp	-0.373***	-0.455***	-0.0837*	-0.251***
	(0.0359)	(0.0378)	(0.0576)	(0.0662)
tran	0.0240**	0.0237**	0.0242**	0.0271**
	(0.0105)	(0.00977)	(0.0114)	(0.0109)
scale	0.354***	0.421***	0.104***	0.151***
	(0.0214)	(0.0238)	(0.0281)	(0.0283)
常数项	1.381***			
	(0.172)			
ρ		-0.390***	0.182**	-0.111*
		(0.0875)	(0.0729)	(0.0847)
sigma2_e		0.0234***	0.00344***	0.00294***
		(0.00183)	(0.000264)	(0.000226)
Sample size	341	341	341	341
R^2	0.635	0.627	0.528	0.001

Table 8. Decomposition Results of Spatial Effects

Variable	Direct effect	Indirect effect	Overall effect
Dec	0.690***	-0.148	0.542**
	(4.20)	(-0.55)	(2.07)
Fdi	-0.188***	-0.070	-0.258**
	(-3.79)	(-0.61)	(-2.15)
fe	-0.028	-0.160***	-0.188***
	(-1.29)	(-2.99)	(-3.60)
gdp	-0.453***	-0.053	-0.506***
	(-11.35)	(-0.54)	(-5.77)
tran	0.022**	0.024	0.046
	(2.23)	(0.87)	(1.63)
scale	0.409***	0.135**	0.544***
	(16.64)	(2.22)	(8.92)
Observations	341	341	341
R-squared	0.627	0.627	0.627

The above-mentioned model is still used to decompose the total effect. As shown in **Table 8**, the direct and indirect effects decomposed by the model regression results are presented. From the perspective of core explanatory variables, the direct effect of the digital economy development level (Dec) is significantly 0.690, while the indirect effect is insignificant -0.149. This indicates that the local digital economy development level only has a significant positive effect on the agglomeration of local high-energy-consuming manufacturing industries, and at the same time, the agglomeration of local high-energy-consuming manufacturing industries is not affected by the digital economy development level of other regions.

3.7. *Discussion*

3.7.1. Further discussion on the individual verification after the addition of control variables

Through the above empirical tests, the spatial effect of digital economy development on the agglomeration of high energy-consuming manufacturing industries has been basically verified. Digital economy development is the most significant influencing factor, while market size and transportation level are positive influencing factors. Developing the digital economy, expanding market size, and further improving the transportation level of the province are important directions for enhancing the agglomeration of high energy-consuming industries. Fiscal expenditure, regional GDP and foreign investment all show negative impacts. For the agglomeration of high energy-consuming industries, it is not the case that the higher the concentration, the better. Instead, it is necessary to control investment and fiscal expenditure. To discuss the impact of different variable combinations on the agglomeration level of high energy-consuming manufacturing industries in provinces, control variables were added one by one to form a test model. The test results are shown in **Table 9**.

Table 9. Results of the time-fixed effect test with control variables added

	Mode(1)	Mode(2)	Mode(3)	Mode(4)	Mode(5)	Mode(6)
Dec	0.926***	-0.163*	-0.188*	0.742***	0.549***	0.670***
	(0.152)	(0.145)	(0.150)	(0.148)	(0.152)	(0.153)
scale		0.143***	0.147***	0.412***	0.404***	0.421***
		(0.0101)	(0.0131)	(0.0244)	(0.0239)	(0.0238)
tran			-0.00767	0.0275***	0.0292***	0.0237**
			(0.0115)	(0.0100)	(0.00976)	(0.00977)
gdp				-0.464***	-0.462***	-0.455***
				(0.0390)	(0.0382)	(0.0378)
fdi					-0.241***	-0.194***
					(0.0510)	(0.0517)
fe						-0.0451**
						(0.0211)
rho	-0.305***	-0.259***	-0.244**	-0.388***	-0.399***	-0.390***
	(0.0989)	(0.0967)	(0.0974)	(0.0877)	(0.0878)	(0.0875)
sigma2_e	0.0616***	0.0379***	0.0377***	0.0261***	0.0247***	0.0234***
	(0.00478)	(0.00293)	(0.00291)	(0.00204)	(0.00196)	(0.00183)

Based on the above test results, the high energy-consuming agglomeration in all provinces has a significant spatial spillover effect. After adding the control variables one by one, the influence directions of each influencing factor have not changed, which also indicates the significance of the core explanatory variables. According to the research results, under the current circumstances, the key to enhancing the concentration level of high energy-consuming industries in provinces lies in: First, promoting the further integration and coordinated development of the digital economy and high energy-consuming manufacturing industries; Second, while controlling the GDP of regions with foreign investment, expand the market scale of manufacturing in the original production areas, and further improve and optimize the construction of transportation facilities

3.7.2. Comparison of Regional Heterogeneity in the Agglomeration Level of High Energy-consuming Manufacturing Industries among Provinces

To further analyze the differences in the agglomeration levels of high energy-consuming manufacturing industries among various provinces, a clustered bar chart was drawn using the location quotient measurement values of high energy-consuming manufacturing industry clusters, as shown in **Figure 10**.

It can be seen that Beijing and Hainan have relatively low levels in the eastern region and throughout the province, while Xizang has the lowest level of agglomeration. This indicates that the market size of its high energy-consuming manufacturing industry is relatively small. The development of high energy-consuming agglomeration levels varies among different regions and provinces. Combined with the spatial spillover of high energy-consuming manufacturing agglomeration among provinces, it is sufficient to demonstrate the complexity of its development situation. Therefore, different provinces should be realistic and control the development of high energy-consuming industries based on specific circumstances.

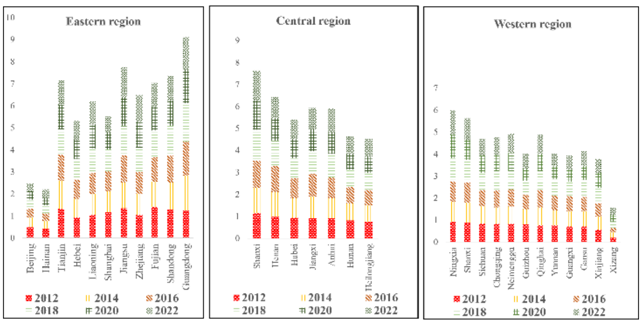


Figure 10. Comparison of the agglomeration levels of high energy-consuming manufacturing industries in the eastern, central and western regions

4. Conclusions

To explore the spatial effect of the digital economy on the agglomeration level of high energy-consuming manufacturing industries, this article mainly relies on the data of 31 provinces in China from 2012 to 2022. By applying the entropy weight method to measure the level of the digital economy and the location entropy to evaluate the agglomeration index of high energy-consuming manufacturing industries, a spatial econometric model is then constructed to analyze the spatial effect of the digital economy on the agglomeration of high energy-consuming manufacturing industries. Through theoretical and empirical analysis, the following research conclusions are drawn:

(1) The development of the digital economy in different provinces of China shows significant heterogeneity. The overall level of digital economy development has gradually improved. However, the digital economy in the central region has developed rapidly, while that in the eastern region is relatively high. There is a significant disparity between the east and the west, which is closely related to regional economic development.

(2) There is regional heterogeneity and complexity in the agglomeration development of high energy-consuming manufacturing industries. Taking the Beijing-Tianjin-Hebei region as a typical example for analysis, the agglomeration level of high energy-consuming manufacturing industries in Tianjin City, Tangshan City and Langfang City has increased significantly, but the overall agglomeration level shows a dispersed trend. The agglomeration level of high energy-consuming manufacturing industries in the western region has gradually increased

(3) The development of the digital economy has effectively promoted the agglomeration of high energy-consuming manufacturing industries. The influence coefficients of the digital economy on the agglomeration of high energy-consuming manufacturing industries are 0.863 and 0.670 respectively, which are significantly positive. The variables of transportation and market size have a promoting effect on the improvement of the agglomeration level of high energy-consuming manufacturing industries, while the variables of foreign investment, fiscal expenditure and per capita GDP show an inhibitory effect.

(4) The digital economy has a positive spatial spillover effect on the agglomeration level of high energy-consuming manufacturing industries. According to the results of empirical tests, the development of the digital economy has a spatial agglomeration effect on the agglomeration level of high energy-consuming manufacturing industries, which is conducive to promoting the high-quality development of China's high energy-consuming industries.

5. Policy recommendations

First, we should strengthen the construction of digital infrastructure, promote digital technological innovation, and facilitate the better development of the digital economy. Local governments attach great importance to the construction of digital infrastructure, support and encourage the research and development and innovation of digital technologies, promote the integration of the digital economy with traditional elements, and facilitate the emergence of new technologies and new business forms. Establish a complete system for cultivating professionals related to the digital economy, accelerate the sharing of digital information in the production process, and promote the high-quality development of various manufacturing industries through the coordination of supply and demand.

Second, enhance the digitalization of industries in the western regions to reduce regional disparities. Expand and extend the digital economy industrial chain from the east to the west, break the unbalanced regional development of the digital economy, promote the development of high energy-consuming industries in resource-rich western regions, and thereby relieve the pressure on traditional industries in the east.

Third, further optimize the transportation network, enhance transportation convenience, reduce the cost of resource transportation, accelerate the operation of high energy-consuming projects, and at the same time strengthen the transportation of new energy to improve the agglomeration level of high energy-consuming industries in each province. The government should issue favorable policies for high energy-consuming enterprises, attract enterprises from other places to flow in, expand the market scale, and thereby promote the agglomeration of high energy-consuming industries.

6. Acknowledgments

This study is one of the phased research results of the National Social Science Foundation project(24BJY037).

7. Conflict of Interest

The authors declare no conflict of interest.

References

Du, C.Z., Liu, S.Z. Measurement and Path Analysis of the Effect of Digital Economy Empowering Total Factor Productivity of China's Manufacturing Industry. Economics and Management Research, 44 (9), 2023.

Fan, H.J., Shen, F.W. High quality development of digital economy: factor functions, main risks, and response strategies. Reform and Strategy, 39 (3), 57, 2023.

Guo, J.S., Chen, B.G. The intrinsic mechanism and policy recommendations of digital economy driving high-quality development of manufacturing industry. Fujian Textile, (4), 43, 2024.

Guo, R., Yuan, Y.J. Research on the impact of Internet development on industrial collaborative agglomeration and its mechanism. Statistical Research, 39 (6), 52-67, 2022.

He, Y.Y., Weng, C.X., Xu, Q.F. Mid-term power load probability density prediction method based on Epanechnikov kernel and optimal window width combination. Power Automation Equipment, 36 (11), 120, 2016.

Li, J., Wang, W. Research on the spillover effects of digital economy empowering high-quality regional development. Modern Management, (2), 10, 2024.

Liao, J.P., Yang, K., Wei, W.T. Research on the Transformation and Development Path of Manufacturing Industry in the Guangdong Hong Kong Macao Greater Bay Area Driven by Digital Economy. Business Economics, (5), 32, 2024.

Liao, X.L., Yang, Z.Y. Measurement and Implementation Path of the Effect of Digital Economy Empowering the Transformation and Upgrading of Manufacturing Industry in the Yangtze River Delta Region. East China Economic Management, 35 (6), 22, 2021.

Liu, C., Pan, H.F., Li, P. Research on the Impact and Mechanism of Digital Transformation on Green Innovation Efficiency of Manufacturing Enterprises. Chinese Soft Science, (4), 121, 2023.

Liu, Y.B., Wang, D.C. Research on the Impact Mechanism of Digitization on Green Transformation of Manufacturing Enterprises. Journal of Shanxi University (Philosophy and Social Sciences Edition), 46 (6), 2023.

Liu, Z.X., Liu, Y.R. Research on the Spatial Spillover Effect of China's Industrial Structure Upgrading on Carbon Emission Intensity. Journal of Wuhan University of Business, 38 (02), 35, 2024.

Ma, S.X., Xu, B., Meng, J. The Mechanism and Heterogeneity Analysis of Digitalization on Manufacturing Agglomeration: Evidence from Smart City Pilot Projects. Industrial Economics Review, 16 (3), 65, 2022.

Pan, B., Zheng, Z.X. The evolution, connotation analysis, and scale measurement of the concept of digital economy. China Economic and Trade Guide, (5), 52, 2022.

Qi, Y.D., Xiao, X. Enterprise Management Transformation in the Digital Economy Era. Management World, 36 (6), 135-152, 2020.

Shen, K.T., Gong, J.J. Environmental Pollution, Technological Progress, and China's High Energy Consuming Industries: An Empirical Analysis Based on Environmental Total Factor Productivity. China Industrial Economy, (12), 2011.

Wang, X.B., Kong, L.X. The Impact of Urban Digital Economy Development on the Agglomeration Level of Manufacturing Industry. Economic Geography, 43 (9), 2023.

Wang, X.L., Han, P. Research on the Coupling and Coordination of China's Digital Economy and Green Development of Manufacturing Industry. Statistics and Decision Making, 40 (1), 10, 2024a.

Wang, Y.Q., Xue, J.X., Fu, J.H. Analysis of the Spatiotemporal Evolution and Regional Differences in the Development Level of China's Digital Economy. Business Economics, (5), 1, 2024b.

Wu, C.Q., Deng, M.L. Research on the Characteristics and Influencing Factors of High Energy Consumption Industrial Agglomeration in the Yangtze River Economic Belt. Technological Progress and Countermeasures, 35 (16), 67, 2018.

Yang, L.K., Yan, K. The impact of digital transformation on pollution emissions of Chinese manufacturing enterprises: a three-dimensional panel data analysis based on micro level. Resource Science, 45 (8), 1481, 2023.

Ye, A.Z., Chen, Z.Y., Li, X.Y. Empirical analysis of the impact of external environment on high energy consuming industries. Statistics and Decision Making, 35 (2), 2019.

Zeng, F.H., Liu, S.P. Empirical test of the impact of "Internet plus" on China's manufacturing upgrading. Statistics and Decision Making, 35 (9), 124, 2019.

Zhao, H.Q., Liu, Y.L. Research on the Coupling and Coordination of Digital Economy and High-Quality Development of Manufacturing Industry. Journal of North China University (Social Sciences Edition), 40 (2), 31, 2024.

Zhong, W.J. The impact of digital economy on the performance of technological innovation in manufacturing industry. Technical Economics and Management Research, (3), 40, 2024.

Zhou, Q. Research on the Impact and Mechanism of Digital Economy on Green Development of Manufacturing Industry. Nanjing Social Sciences, (11), 2023.