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Research on the Influence Mechanism of Digital Economy on Energy Consumption Structure Under the Target of "Double-carbon"

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Abstract: Facing the increasingly severe resources and ecological problems, China has included the development of "green economy" in the development strategy. At present, China is experiencing a new round of energy reform with the dual effects of ecological and social. In order to solve the shortage of petrochemical resources and achieve the goal of "carbon reduction", the new round of energy conservation reform aims to increase the energy consumption of clean energy. Therefore, this study in the under the background of "double carbon" target, through the relevant research results at home and abroad, the energy industry development in China made a comprehensive analysis, qualitative analysis of energy consumption of green economy development mechanism, and adopt the entropy right Topsis model, space measurement model respectively in 2011-2021 our country provincial panel data empirical analysis, to explore the mechanism of energy consumption mechanism to promote the optimization of energy consumption structure in our country, realize the sustainable development.

Keywords: "Two-carbon" target, Digital economy, Energy consumption structure.

1. Introduction

With the rapid development of digital technologies such as the Internet, cloud computing, IoT, and blockchain, the digital economy is the main driving force for the recovery of the world economy after COVID-19, and also the main force for changing the world economic pattern. With the rapid development of science and technology today, the digital economy has become an indispensable and new economic form. It has driven our economy to take off at an alarming speed, especially under the influence of the current epidemic, and has played an important role. The 14th Five-Year Plan is an important node for China to cope with global warming and reach the peak of carbon emissions. Meanwhile, it will also become an important five years for China's industry to achieve green and low-carbon development, and will lay a good foundation for China to achieve the peak of carbon emissions in 2030. Through digital transformation and the use of advanced technology, the efficiency of energy, resource and environmental management is greatly improved, providing a strong support for the realization of green manufacturing. With the continuous transformation and development of China's economy, the environmental protection concept of "clear waters and green mountains are gold and silver mountains" has been widely recognized and widely accepted. With the rapid development of the digital economy, it has penetrated into our daily life, providing a strong support for China's economic structural adjustment and future development.

At present, the research on the development of digital economy is in the initial stage, and there are still a lot of research value potential to be explored. There are few studies on the impact of digital economy on the energy consumption structure. At present, the research is more on the impact of the development of digital economy on the high quality of the economy and the development of various industries, but a specific theoretical framework has not been formed. Digital economy as the main driving force of the current economic development in our country, and green development as the main development direction of economic development, need to study the internal relationship between the two, and the digital economy to promote the transformation of energy consumption structure mechanism, will be to the future human high quality economic development and environmental protection play a dual role.

On the other hand, historical experience has proved that the development of digital economy has laid an industrial foundation for the change of energy consumption structure, and provided the data foundation along with the development of digital technology and technical support. In recent years, the application of digital technology can make it more convenient for the government to collect the thoughts and demands of the people and enterprises for environmental protection, timely adjust the direction of the government's environmental protection work, and formulate more appropriate environmental protection policies, so as to contribute to the change of energy consumption structure. This study continues to dig down on the level of energy conservation and emission reduction, and focuses on the energy consumption structure. Through the analysis of the energy consumption structure, it clarifies the development relationship between the digital economy and the energy consumption structure, and coordinates the relationship between the economy and the environment in the transformation of the digital economy.

2. Research Status

The core value of the digital economy is that it uses data and information to drive the economy and achieve faster growth through continuous innovation. Its advantages include: reliable data, predictable markets, controllable prices, and manageable resources, thus improving the overall economic efficiency. Wang Juanjuan (2021) pointed out that the emergence of the digital economy has greatly changed human values and economic activity patterns. Chen Xiaohong et al. (2021) pointed out that digital economy is an economic activity based on digital information (including data elements), supported by the Internet platform, with digital technology innovation as the driving force, and represented by a variety of new models and business forms. Wang Jun et al. (2021) pointed out that the emergence of digital economy is not only based on data production, but also benefits from the effective application of information and communication technology and artificial intelligence, which provides new possibilities for global economic growth, and also provides feasible solutions for eliminating the gap between countries and regions.

An average proportion of resource utilization on the high side, the reason is its huge population, and oil, gas dependence is increasing, which makes the traditional coal energy has been unable to meet the needs of the in today's world, therefore, we must try to find more clean, more efficient energy, and optimize the structure of energy consumption (Lu Jialiang, 2013). Zheng Cui pointed out that the discovery of "poor in oil, less in gas and relatively rich in coal" shows that coal accounts for more than 94 percent of China's three major mineral energy and mineral resources reserves. The proportion of oil and natural gas is only 6%, so due to the scarcity of resources, China's energy consumption structure will still take coal as the main source. Researcher Yuan Yijun et al. (2012) studied the regional and temporal differences of energy consumption in China through a variety of methods. Researcher Zou Xuan (2019) found that different industrial structures can have different effects on energy consumption.

By studying how regional integration affects the relationship between the digital economy and energy consumption, their research shows that the effect is significant, and that the effect leads to a negative link between the two. Wei Lili, et al. (2022) used panel model and Tobit model and found that digital economy has a significant positive impact on urban green development. Han Jing et al. (2022) used Chinese urban panel data and found that the digital economy can enable green development.

According to the latest research results, with the development of the digital economy, its influence is growing, and people are becoming more and more concerned about saving resources and achieving sustainable development. Information and communication technology is the core of the digital economy. It can not only improve the efficiency of energy use, but also efficiently reduce carbon emissions, providing a strong support for the development of low-carbon and green economy. However, the digital economy does not always have a positive impact on energy consumption. In the early stages of the digital industry, it needs to consume a lot of electricity, which leads to increased carbon emissions and a negative impact on the environment. Research shows that the digital economy has had a profound impact on energy consumption. Many scholars are trying to explore this problem, and have achieved many significant research results. In the future, we will continue to explore how the digital economy will change energy consumption, and in which areas it will have a greater impact. Currently, many studies focus on the field of ICT and data analysis, but future research will expand to other areas. Second, many studies focus on how the digital economy changes the geographic distribution of energy consumption, but future studies will focus on how data analysis changes the geographic distribution of energy consumption. Third, many studies will explore how the digital economy changes the social structure of energy consumption and in which areas it will have a greater impact. As the digital economy evolves, its impact on energy consumption can be significant or potential, and this effect can be achieved through some complex intermediary mechanisms. To better understand how the digital economy affects energy consumption, we have to study three areas in more detail.

3. The Empirical Study Design

3.1. Interpretive variables

In 2005, the Atomic Energy Agency (IAEA), the United Nations Department of Economic and Social Affairs (UNDESA), the Energy Agency (IEA), the European Community Statistics Agency (Eurostat) and the European Environmental Protection Agency (EEA) (EED) (EUROSTATE) worked together to develop a structural index system for energy consumption (EISD). The number of indices is over 300, including economic, social and environmental aspects. In this paper with the sustainable development of the index system as the theoretical basis, and associated with the reality of energy consumption structure, according to the main research problems in this paper, we selected the energy consumption elasticity coefficient, carbon dioxide emissions per unit GDP, energy processing conversion efficiency, energy self-sufficiency rate the four indicators to comprehensive evaluation.

Among them, energy consumption elasticity refers to the change of energy consumption of a country or region in a certain year, reflecting the change of energy consumption of a country or region in a year, and can be used to measure the change of the economic development level in the region. Due to China's economic growth, the consumption of energy also increases, and this change can be reflected by observing the correlation between energy consumption and economic development. By analyzing the annual average growth rate of the national economy, we can infer the changing trend of energy consumption, and thus obtain the elasticity coefficient of energy consumption. By combining unit GDP with gross national income, China's actual economic development level and greenhouse gas emissions can be more accurately reflected, so as to better meet people's well-being needs. Processing conversion can greatly improve the effective degree of energy use in a certain period of time. Turn the original energy sources into more new energy sources, so that the total amount of energy products produced is greatly increased. This index can be used to measure the technical level of the energy processing and conversion device, as well as its advancement and perfection in the production process. According to the calculation results, the energy processing conversion efficiency can be expressed by multiplying the total amount of processing and conversion / the total input of conversion by 100. Energy self-sufficiency rate: energy self-sufficiency rate =1-energy consumption and import rate.

3.2. Core explanatory variables

At present, there is no international standard for the selection and measurement method of digital economy index, and there is no unified digital economy measurement index as the normative guidance. For example, at the IMF (IMF) Statistical conference, on the theme of "metrological digital economy", it was mentioned that there is no statistical method to measure the marginal contribution of the digital economy to manufacturing products and services. The Digital Economy

Competitiveness Index proposed by the Shanghai Academy of Social Sciences analyzes the development of the world's digital economy from four dimensions: infrastructure construction, industrial scale, innovation ability and governance evaluation. The measurement method of digital economy has been attracting the attention of various government agencies, including DEBA (Digital Economy Advisory Board of the US Department of Commerce), OECD (Organization for Economic Cooperation and Development), BEA (US Department of Commerce), EU (EU), etc. However, no method has been widely accepted; the limitations of the digital economy proposed by international organizations is limited.

This paper in liu (2020), liu and Chen (2021), on the basis of the work of the existing urban data, according to the requirements of scientific, normative and concise, from the "digital facilities", "Internet application", "digital industry development" and "digital finance" four dimensions, build a digital economy development level index system, and has carried on the empirical analysis, specific as shown in table 1. The Digital Financial Development Level Index jointly launched by Peking University Digital Finance Research Center and Ant Financial Services Group aims to measure the popularity of digital technology in the financial field to better meet the financial needs of consumers. With the continuous progress of mobile communication technology, the number of Internet users increases, the development of digital economy depends on the growth of various industries, such as the revenue of software and information services, number of employment, e-commerce and commodity production.

Table 1. Index measurement system of digital economy development level

Level 1 indicators	Secondary indicators	Measurement index	Index unit	Indicator attributes
Digital economy development level index measurement	Digital facilities	Optical cable length	kilometre	+
		Number of Internet broadband access ports	Ten thousand	+
		Internet domain name number	Ten thousand	+
	Internet applications	Number of mobile phone base stations	Ten thousand	+
		Mobile phone penetration rate	Department / 100 people	+
		Internet penetration rate	%	+
		The number of Internet users	thousands of people	+
	Digital industry development	Software industry revenue	Wan Yuan	+
		Number of employees in the information services industry	thousands of people	+
		Output value of the information services industry	100 million	+
		Telecom business volume	100 million	+
	Digital finance	The Digital HP Financial Index	/	+

The above materials are from China Urban Statistical Yearbook, China Regional Statistical Yearbook, 2011-2021 statistical Yearbook of all provinces and cities, as well as CNRDS "China Survey Data Service Platform" (Management Home) and "EPS Global Statistics" (EPSGlobalInformationPlatform). For the absence of individual data, we used interpolation and used the intermediate method to fill in.

Regarding the evaluation method, the TOPSIS model based on entropy weight is constructed, and the results are shown in Table 2:

From the perspective of temporal trend, the overall digital economy level of the Yangtze River Delta urban agglomeration is higher than that of other regions, and the development level of the eastern region is higher than that of the western region. Among them, Beijing, Shanghai, Jiangsu, Zhejiang and Guangdong are far ahead of other provinces in terms of digital economy comprehensive index. It can be seen that the development level of China's digital economy is still polarized, the "gap between the rich and the poor" is more obvious, and the "digital divide" is more serious (Yan Hui, 2012).

4. Measurement Results and Analysis

4.1. Exploratory analysis of energy consumption structure —— spatial correlation test

A spatial correlation analysis of the variables is required before considering the spatial modeling. Spatial heterogeneity reflects the instability of the relationship between spatial units, regional innovation of enterprises, universities, research institutions in the digital economy development and green innovation activities exist individual differences, the differences may lead to variables on the geographical space interdependence or local club effect. The Moran index is a common method for analyzing spatial correlations.

4.1.1. Brief description of the calculation method

The magnitude of the global Moran index reflects the clustering and dispersion of the index in the global.

The MoranI (Global Moran Index) is defined as follows:

$$\text{Moran I} = \frac{\sum_{i=1}^{n}\sum_{i=1}^{n} w_{ij}\left(y_i - \bar{y}\right)\left(y_j - \bar{y}\right)}{s^2 \sum_{i=1}^{n}\sum_{i=1}^{n} w_{ij}} \tag{1}$$

among:

$$s^2 = \frac{1}{\mathrm{n}}\sum_{i=1}^{n}(y_j - \bar{y}), \bar{y} = \frac{1}{\mathrm{n}}\sum_{i=1}^{n} y_{\mathrm{i}} \tag{2}$$

Table 2. The development degree of digital economy level in domestic provinces from 2011 to 2021

province	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Anhui	0.756	0.772	0.788	0.808	0.847	0.872	0.905	1.012	1.111	1.165	1.121
Beijing	1.161	1.223	1.295	1.379	1.505	1.605	1.674	1.946	2.164	2.367	1.696
Chongqing	0.754	0.771	0.791	0.814	0.839	0.863	0.889	0.950	1.021	1.063	0.899
Fujian	0.837	0.863	0.872	0.912	0.986	1.093	1.237	1.306	1.356	1.267	1.262
Gansu	0.714	0.721	0.728	0.734	0.749	0.755	0.773	0.812	0.848	0.877	0.828
Guangdong	1.203	1.307	1.400	1.501	1.648	1.755	1.879	2.311	2.640	2.875	2.368
Guangxi	0.739	0.750	0.760	0.776	0.800	0.815	0.840	0.910	1.010	1.070	0.964
Guizhou	0.726	0.734	0.745	0.753	0.775	0.787	0.818	0.885	0.976	1.021	1.017
Hainan	0.704	0.709	0.717	0.723	0.733	0.734	0.750	0.773	0.800	0.800	0.831
Hebei	0.789	0.807	0.822	0.838	0.872	0.897	0.933	1.044	1.138	1.175	0.942
Heilongjiang	0.741	0.749	0.780	0.790	0.800	0.797	0.822	0.845	0.885	0.906	0.885
Henan	0.786	0.806	0.835	0.869	0.920	0.952	0.990	1.170	1.292	1.375	1.068
Hubei	0.779	0.801	0.830	0.857	0.920	0.934	0.960	1.088	1.195	1.231	1.061
Hunan	0.775	0.791	0.807	0.831	0.863	0.904	0.934	1.015	1.133	1.191	1.022
Jiangsu	1.075	1.154	1.232	1.326	1.444	1.534	1.635	1.766	1.943	2.059	1.355
Jiangxi	0.738	0.748	0.758	0.772	0.799	0.811	0.843	0.913	0.995	1.030	0.918
Jilin	0.749	0.756	0.761	0.771	0.783	0.796	0.814	0.845	0.870	0.890	0.835
Liaoning	0.852	0.883	0.919	0.948	0.975	0.945	0.967	0.999	1.065	1.101	1.085
Nei Monggol	0.732	0.741	0.749	0.756	0.765	0.773	0.794	0.821	0.865	0.888	0.842
Ningxia	0.698	0.703	0.706	0.710	0.714	0.719	0.726	0.740	0.751	0.758	0.825
Qinghai	0.697	0.702	0.705	0.708	0.712	0.714	0.720	0.734	0.744	0.754	0.857
Shandong	0.926	0.956	1.101	1.118	1.154	1.187	1.225	1.387	1.516	1.594	1.271
Shanghai	0.965	1.007	1.037	1.074	1.141	1.181	1.222	1.347	1.466	1.563	1.139
Shanxi	0.749	0.757	0.766	0.778	0.793	0.804	0.824	0.882	0.918	0.950	0.918
Shaanxi Province	0.765	0.777	0.793	0.810	0.835	0.852	0.877	0.954	1.028	1.069	0.921
Sichuan	0.867	0.894	0.929	0.976	1.050	1.095	1.160	1.266	1.408	1.535	1.189
Tianjin	0.750	0.766	0.780	0.799	0.817	0.839	0.854	0.878	0.925	0.962	0.846
Yunnan	0.747	0.759	0.770	0.782	0.807	0.815	0.846	0.917	1.008	1.068	1.026
Zhejiang	0.915	1.039	1.016	1.090	1.233	1.334	1.418	1.598	1.792	1.923	1.399

y_i i n ω_{ij} n It is the observation value of the selected ground, the total number of spatial units, and the binary spatial weight matrix, which reflects the spatial region proximity of a spatial unit, and determines the weight size of the unit in space.

$$w = \begin{bmatrix} w_{11} & w_{12} & \cdots & w_{1n} \\ w_{21} & w_{22} & \cdots & w_{2n} \\ \mathrm{C} & \mathrm{C} & \mathrm{E} & \mathrm{C} \\ w_{n1} & w_{n2} & \cdots & w_{nn} \end{bmatrix} \tag{3}$$

Generally, according to whether the two units are adjacent, its value is ω_{ij}

$$w_{ij} = \begin{cases} 1 \\ 0 \end{cases} \tag{4}$$

$w_{ij} = 1$ representation;.Current region i is adjacent to the j，

$w_{ij} = 0$ Current region i is adjacent to the j

MoranI Is the product sum of observations in each region, and its values range in [-1,1].

$$\text{Moran I} = \begin{cases} > 0 \\ = 0 \\ < 0 \end{cases} \tag{5}$$

MoranI> 0 means that the larger the value, the more significant the aggregation effect; MoranI=0 indicates no spatial correlation; MoranI <0 means that the smaller the value, the more significant the discrete benefit. After calculating the MoranI, the hypothesis needs to be tested: all study subjects are randomly distributed in space. H_0

$|z| > 1.96$ Under the significance level of 0.05, the null hypothesis can be rejected if it is met or a p-value <0.05. There is good reason to think that the Moran index is significant, and there is spatial aggregation or spatial discrete effect in the global.

After the global Moran index is significant, the local Moran index calculation is still needed. The local Moran index can reflect where the index is significant and determine the location where the global Moran index is not significant or 0, the local Moran index can reflect whether the index has aggregation or discrete effect in local space, respectively.

$$\text{Local Moran index}=\begin{cases}\text{high aggregation}\\ \text{high - low aggregation}\\ \text{low aggregation}\\ \text{low - high aggregation}\end{cases} \tag{6}$$

Calculation formula: (with the same meaning as the global Moran index)

$$I_i = \frac{z_i}{s^2}\sum_{j\neq i}^{n}\omega_{ij}Z_j \tag{7}$$

4.1.2. Calculate the structure and process

Adjacency method is generally used in global Moran calculation, which requires two regions to have common boundaries or nodes to be counted as adjacent elements. According to the empirical formula, if the calculation results are required to have good credibility, at least 30 spatial units are required to ensure that each unit has enough adjacent elements. There are 29 units in the study area of this paper, and the data have a certain bias, so here we can improve the calculated accuracy threshold to increase the proximity elements of each unit and increase the credibility of the analysis results.

The calculation process is implemented by ArcGIS and GeoDa software. According to the p-value and z-value in the test results, the two variables can be considered to have a relatively significant spatial correlation at the 95% significant level, that is, to reject the null hypothesis. Figure 9, Figure 10, and Table 2, Table 3, show the global Moran index and local clustering map results for the digital economy level and energy consumption structure in 2011,2016 and 2021, respectively.

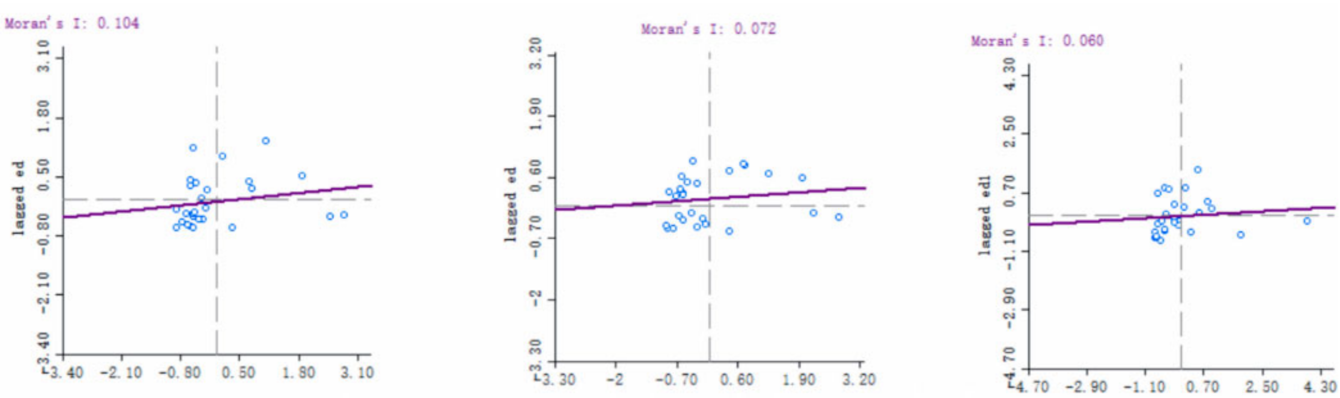

Figure 1. The Global Moran index of the digital economy level

Table 2. Local clustering results of the digital economy level

	First quadrant (H-H)	The Second Quadrant (L-H)	Third quadrant (L-L)	Fourth quadrant (H-L)
In 2011,	Guangdong, Zhejiang, Beijing, Tianjin, Shanghai	Anhui, Fujian, Hebei, Jiangxi, Shandong, Shaanxi, Shanxi	Inner Mongolia, Gansu, Guangxi, Guizhou, Henan, Jilin, Liaoning, Ningxia, Qinghai, Yunnan	Sichuan, Chongqing, Jiangsu, Hubei, Hunan
In 2016,	Guangdong, Zhejiang, Beijing, Tianjin, Hebei, Jiangsu, Shanghai	Anhui, Fujian, Henan, Jiangxi, Shandong, Shaanxi, Shanxi	Inner Mongolia, Gansu, Guangxi, Guizhou, Henan, Jilin, Ningxia, Qinghai, Yunnan	Sichuan, Chongqing, Hubei, Hunan, Liaoning
In 2021,	Guangdong, Zhejiang, Fujian, Beijing, Tianjin, Hebei, Jiangsu, Shandong, Shanghai	Jiangxi, Anhui, Guangxi, Guizhou, Jiangxi, Shaanxi, Shanxi	Inner Mongolia, Yunnan, Gansu, Ningxia, Qinghai, Yunnan	Sichuan, Chongqing, Hubei, Hunan, Jilin, Liaoning

The results show that the global Moran index of digital economy from 2011 to 2021 decreased from 0.104 to 0.060, indicating the development of digital economy; the development of digital economy in provinces showed low concentration in the north and low concentration in the west in 2011. By 2021, the development in the east showed high concentration.

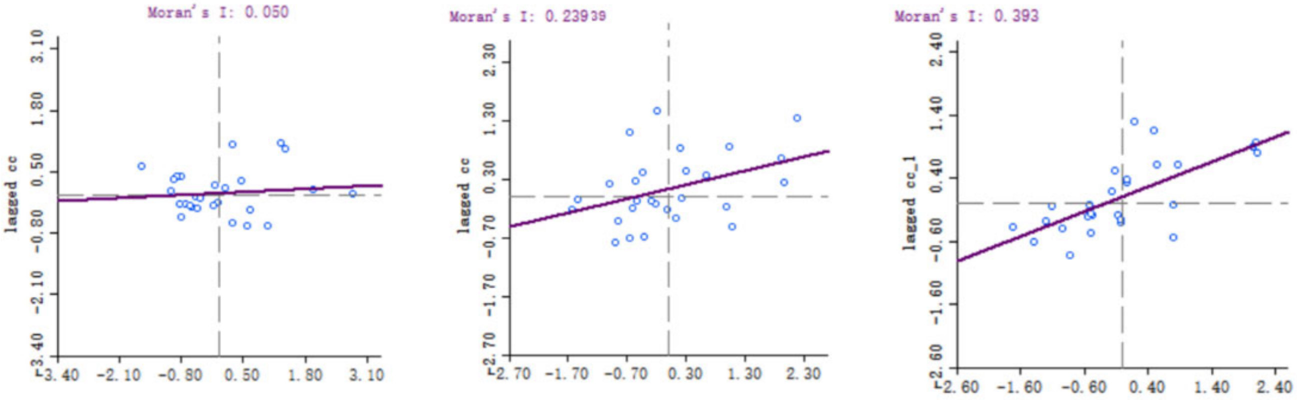

Figure 2. The Global Moran Index of the energy consumption structure

Table 3. Local clustering results of the energy consumption structure

	First quadrant (H-H)	The Second Quadrant (L-H)	Third quadrant (L-L)	Fourth quadrant (H-L)
In 2011,	Inner Mongolia, Gansu, Guizhou, Henan, Jilin, Liaoning, Ningxia, Qinghai	Anhui, Fujian, Hebei, Jiangxi, Shaanxi, Shanxi	Guangdong, Zhejiang, Beijing, Tianjin, Shanghai, Yunnan, Shandong	Sichuan, Chongqing, Jiangsu, Hubei, Hunan, Guangxi
In 2016,	In Inner Mongolia, Gansu, Guizhou, Ningxia, Qinghai	Anhui, Fujian, Henan, Jiangxi, Shaanxi, Shanxi, Jilin	Guangdong, Zhejiang, Beijing, Tianjin, Hebei, Jiangsu, Shanghai, Yunnan, Shandong	Sichuan, Chongqing, Hubei, Hunan, Liaoning, Guangxi, Henan
In 2021,	Inner Mongolia, Gansu, Ningxia, Qinghai	Jiangxi, Anhui, Guangxi, Jiangxi, Shaanxi, Shanxi, Jilin	Guangdong, Zhejiang, Fujian, Beijing, Tianjin, Hebei, Jiangsu, Shandong, Shanghai, Yunnan	Sichuan, Chongqing, Hubei, Hunan, Liaoning, Guizhou, Henan

The results show that during the period from 2011 to 2021, the global Moran index of energy consumption structure increased from 0.239 to 0.393, indicating that the discrete of energy consumption structure in domestic provinces has decreased. In 2011, the development of energy consumption structure showed the state of high and high aggregation in the northwest and low and high aggregation in some neighboring provinces. In 2021, the state of high and high aggregation in the north will continue to expand and spread to the inland.

4.2. Spatial measurement and regression analysis

4.2.1. Brief description of the calculation method

After examining the spatial correlation of variables, this paper constructs the spatial lag model and the spatial error model, and develops a series of regression analysis of both. The specific process is implemented by ArcGIS and GeoDa software.

(1) Spatial lag model (SAR)

The spatial lag model is to extend the general model to the space field and add some spatial variables for regression. The lag variable considers the time series, and the spatial lag considers the effect of the surrounding region on the study area. The model form is as follows:, the explanatory variable matrix, coefficient, the parameter vector, and the spatial weight matrix. After the deformation expansion, the following formula: $y = \rho\omega y + x\beta + \varepsilon$ x ρ β ω

$$\ln F_i = \alpha_0 + \alpha_1\omega_{iJ}\ln F_i + \alpha_2\ln F_1 + ... + \alpha_4\ln F_i \ + \varepsilon_{it} \quad (8)$$

$\ln F_i$ ω_{iJ} α_1 Taking the logarithm of the energy consumption structure as the explained variable in the model, the spatial weight matrix in the Moran index is used as the spatial autoregression coefficient, reflecting the effect and direction of the spatial lag term, and the disturbance term with spatial dependence. ε_{it}

(2) Spatial error model (SEM)

The spatial perturbation correlation and the spatial population correlations are described to measure the direction and extent of the error impact of the adjacent individual on the observed value of the interpreted individual. It means that when the parameters of a region change significantly, its effect will spread to the adjacent region in the form of covariance structure, which is persistent and gradually weakened. The model form is shown as follows:

$$y = x\beta + \varepsilon \quad (9)$$

$$\varepsilon = \gamma\omega\varepsilon + \mu \quad (10)$$

$$\mu \sim N\left(0, \sigma^2 I_n\right) \quad (11)$$

γ ω Where, it is the spatial error correlation coefficient, which is the spatial weight matrix in the Moran index above, which is the same as the expansion form of the model SAR. The expansion gives the following formula:

$$\ln F_i = \alpha_1 \ln F_i + ... + \alpha_3 \ln F_i \ + \gamma\omega_{ij} + \varepsilon_{it} \quad (12)$$

$\ln F_i$ ω_{iJ} α_1 ε_{it} Also the logarithm of the energy consumption structure, the spatial weight matrix in the Moran index is used, which is the spatial autoregression coefficient, reflecting the action effect and direction of the spatial lag term, and the disturbance term with spatial dependence. Different from the SAR model, the disturbance term of the SEM model has spatial dependence. ε_{it}

4.2.2. Calculation process and process

It has been proved that there is spatial correlation in the energy consumption structure of 29 provinces in China. In order to determine the relationship between the correlation and the lag term and the error term, that is, whether to choose the spatial lag model or the spatial error model, the spatial measurement model is selected by LM test. The text only gives the test results for some periods, as shown in Table 4:

Table 4. Results of the LM test for spatial correlation

LM checkout	period	statistics	P price
LMLAG	2011	41.157	≤0.001
RobustLMERR		13.406	≤0.001
LMERR		28.006	≤0.001
RobustLMERR		5.406	0.034
LMLAG	2016	46.330	0.013
RobustLMERR		11.741	≤0.001
LMERR		32.697	≤0.001
RobustLMERR		8.235	0.021
LMLAG	2021	42.256	≤0.001
RobustLMERR		10.406	0.009
LMERR		34.262	≤0.001
RobustLMERR		6.571	0.013

Anselin and Florax argue that LMLAG has higher statistical significance than LMERR, while RobustLMLAG has higher LMERR and RobustLMERR has no higher correlation, it is more suitable to the spatiotemporal delay mode; conversely, if the ERR of the LM is larger than the LM and the LMLAG value, the spatial deviation model is more suitable. According to Table 2, the statistical values of LMLAG and LMERR are significant and less than 0.05, indicating that the spatial measurement model is more appropriate.

Then the data were tested for spatial lag and spatial error, and the results are shown in Table 5.

Table 5. Results of the spatial estimation of the energy consumption structure by the digital economy

variable	period	SAR model	SEM model
cofficient	2011	-1.051	-0.732
ρ / λ		0.621	0.613
R^2		0.531	0.494
Log-likelihood		-4.532	-6.714
Akaikeinfocriterion		15.062	17.428
Schwarz criterion		18.953	20.019
cofficient	2016	-1.349	-1.422
ρ / λ		0.581	0.661
R^2		0.456	0.421
Log-likelihood		-12.142	-13.528
Akaikeinfocriterion		30.285	31.055
Schwarz criterion		34.282	33.719
cofficient	2021	-1.491	-1.352
ρ / λ		0.648	0.558
R^2		0.422	0.412
Log-likelihood		-11.036	-11.560
Akaikeinfocriterion		28.071	27.120
Schwarz criterion		31.959	29.712

By comparing SAR model and SEM model, the coefficient of explanatory variables (digital economic level index) has the same sign, indicating that the regression results are relatively robust. After experimental testing, the fitting accuracy of the SAR model significantly exceeds the SEM model, and the data of the natural log-likelihood function also shows good accuracy. Therefore, therefore, we can safely use the SAR model.

The analysis of the empirical results of the model shows that the urban digital economy level has a negative effect on the energy consumption structure, and the energy consumption structure will continue to transform with the development of the level of the digital economy, the absolute coefficient of its influence on the energy consumption structure increases year by year, from-1.051 in 2011 to-1.491 in 2021. Meanwhile, the spatial error coefficient λ is positive, indicating a significant spatial dependence between the level of digital economy and the energy consumption structure. Can be seen from the pattern, on 1% is significant for positive, it shows that in the adjacent contact cannot ignore the role of region and region, and in the study, also can see the role of the role of the region and the region, therefore, the digital economy broke the regional restrictions, and has a kind of influence on its. That is to say, when the regional digital economy drives the transformation of local energy consumption structure, it will also drive the development of energy consumption structure in surrounding areas. ρ

5. Conclusion and Recommendations

This paper based on 29 provinces 2011-2021 samples, first using the entropy method of the digital economy level evaluation of the provinces, then, through the space exploratory analysis method —— moran index of energy consumption structure of spatial clustering and spatial autocorrelation analysis, after determining the energy consumption structure of spatial correlation, establish spatial measurement model analysis, test the influence of digital economy on energy consumption structure.

Based on the spatial measurement method, this paper tests the impact of the development of digital economy on the change of energy consumption structure. According to the results of the study, The improvement of the digital economy can drive the transformation of the energy consumption structure, first, From a global spatial perspective, The law of the energy consumption structure is similar to the global effect of the digital economy, The energy consumption structure of each province has a significant spatial correlation and decreases with time, Reduced from 0.239 in 2011 to 0.393 in 2021, That is, the coordination of energy consumption activities among various cities, The overall difference within the region is narrowed, follow, By comparing the eastern, central, western, and northeastern regions, As we can see, Data from different regions have different effects on the development of low-carbon industries, While the eastern, central and western regions are relatively small, The difference between the eastern and western regions is relatively large. Especially in the eastern and western regions, the development level of digital economy has a higher influence on the development of energy consumption structure than that in the central regions. To sum up, the digital economy is improving the industrial structure and making a significant contribution to the improvement of the energy consumption structure after enhancing the technological innovation capacity. In recent years, the country began to pay attention to the application of clean energy power generation, but it still has not reached a high level. And urbanization and the improvement of the level of education for the reduction of energy consumption structure has a significant effect, this may be because the urbanization level and education level on the one hand, improve the overall quality of residents, make residents pay more attention to environmental protection and clean energy consumption, at the same time, also enhance the level of local technology research and development, promote the promotion of local industrial structure, thus reducing the use of conventional energy such as coal.

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