International Journal of Economics, Finance and Management Sciences
2022; 10(3): 134-149
http://www.sciencepublishinggroup.com/j/ijefm
doi: 10.11648/j.ijefm.20221003.16
ISSN: 2326-9553 (Print); ISSN: 2326-9561 (Online)

The Impact of the Digital Economy on China's Carbon Emissions

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To cite this article:
Xinman Lv, Hang Yu, Ying Zhang. The Impact of the Digital Economy on China's Carbon Emissions. *International Journal of Economics, Finance and Management Sciences*. Vol. 10, No. 3, 2022, pp. 134-149. doi: 10.11648/j.ijefm.20221003.16

Received: May 28, 2022; **Accepted**: June 14, 2022; **Published**: June 27, 2022

Abstract: As a new format, the digital economy will inevitably affect the environment while bringing economic benefits. To explore the mechanism, regional differences of the digital economy on carbon emissions, and provides a theoretical basis for the realization of the carbon peaking and carbon neutrality goals of the digital economy. This paper selects China's provincial panel data from 2011 to 2019, constructs an indicator system to scientifically measure China's digital economy development level and carbon emission level, and uses the spatial Durbin model to study and analyze the impact of digital economic development on carbon emissions. The results show that: (1) there is a positive spatial correlation between China's carbon emissions. The development of the digital economy has an inhibitory effect on carbon emissions in both local and adjacent areas, and the effect of locality is greater than that of adjacent areas. (2) there are obvious regional differences in the relationship between digital economy development and carbon emissions in China. The development of digital economy in eastern and central China has a significant inhibitory effect on carbon emissions. However, the inhibitory effect in the central region is slightly stronger than that in the eastern region, and the development of the digital economy in the western region has not yet shown a significant effect on carbon emissions. (3) According to the results of spatial Durbin model, digital economy development in eastern China has a significant negative spillover effect on carbon emissions, while that in central China has a significant positive spillover effect. The research helps to plan the development strategy of the digital economy according to local conditions, implement low-carbon policies according to the right medicine, and effectively alleviate the problem of unbalanced development in different regions.

Keywords: Digital Economy, Carbon Emissions, Carbon Neutrality, Spillover Effects, Spatial Dubin Model

1. Introduction

Global warming is a huge challenge facing all mankind. The continued increase in greenhouse gas emissions will have a negative impact on agricultural production, socio-economic activities and human life, thereby hindering the progress of global sustainable development [1]. China's economy has shifted from a stage of high-speed growth to a stage of high-quality development, and the traditional growth model at the expense of energy consumption has become weak in driving the economy. At the same time, facing the pressure of international carbon emission reduction, the ecological environment has increasingly become a livelihood issue that cannot be ignored. According to the statistics of the "World Energy Statistical Yearbook 2021" [2], from 2010 to 2020, China's carbon emissions increased from 8.146 billion tons to 9.899 billion tons, accounting for a large proportion of the world's total carbon emissions, and the emission reduction situation is grim. In view of the responsibility of carbon emission reduction in the context of global warming and the issue of environmental effects in socio-economic development. In September 2020, President Xi Jinping pledged at the UN General Assembly to achieve carbon peaking and carbon neutrality by 2030 and 2050, respectively. China's carbon peaking and carbon neutrality goals show that China prioritizes reducing greenhouse gas emissions, expresses its determination to mitigate climate change. And it also meets the essential requirements of China's high-quality development, and strives to transform towards green and sustainable development [3].

As an important symbol of the era of industry 4.0, digital economy takes data as the key production factor, digital technological innovation as the core driving force, modern information network as an important carrier, open and win-win as the mainstream development mode, and multiple co-governance as the core governance mode [4]. Utilize emerging technologies such as big data, artificial intelligence, 5G, cloud computing, blockchain, and the Internet of Things to continuously promote productivity improvement and high-quality economic development [5]. The digital economy has increasingly become a crucial element of economic development, and it plays an irreplaceable role in expanding internal demand, enhancing endogenous power, enhancing scientific and technological innovation capabilities, and strengthening the national new infrastructure strategy. It provides a steady stream of impetus for the innovation, green, high-quality, and sustainable development of the national economy in the new era, and has become the core force leading technological change, industrial change, and the evolution of the international competition pattern [6].

Since the sudden outbreak of the COVID-19 in 2020, The world is actively exploring new offices, education, production, and lifestyles to promote the vigorous development of the digital industry. The digital economy is shining brightly, showing great development potential and tenacious vitality. According to the survey data released by the China Academy of Information and Communications Technology (CAICT), the scale of China's digital economy is still in a booming development trend in 2020. Its overall scale is as high as 39.2 trillion yuan, an increase of 3.3 trillion yuan compared with 2019, accounting for 38.9% of GDP, and the growth rate is 3.2 times higher than the nominal GDP growth rate over the same period, maintaining a growth level of 9.7%. From the perspective of the internal structure of the digital economy, digital industrialization accounts for 19.1% of the digital economy, while industrial digitalization accounts for 80.9%, accounting for 7.3% and 31.2% of GDP respectively, laying the foundation for the further improvement of the digital economy. In the context of the gradual normalization of the prevention and control of the COVID-19, the digital economy has become an important engine for China's economic development. Digital information technology has gradually become the core competitiveness of China to accelerate development, enhance its international status, and stand in the forest of international economy. However, while the overall development of the digital economy is growing rapidly, some problems have gradually emerged in regional development. On the one hand, there are differences in digital technology level, data factor endowment, and digital infrastructure among regions [7]. On the other hand, the spatial non-equilibrium characteristics of regional development will lead to the spatial heterogeneity of the development of the digital economy. Therefore, the level of regional economic development and industrial structure upgrading is the internal driving force for the development of the digital economy [8].

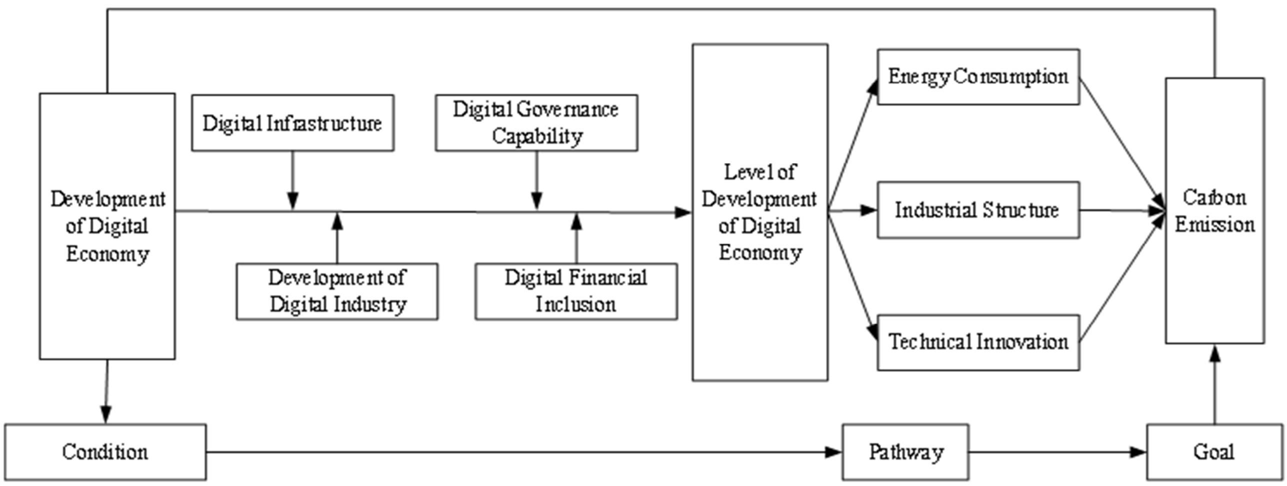

Figure 1. *The impact mechanism of digital economy development on carbon emission.*

China's "14th Five-Year Plan" and the outline of the long-term goals for 2035 propose to accelerate the construction of a digital economy, a digital society, and a digital government, and activate the potential of data elements. It further clarified the development principles of the digital economy, accelerated the construction of digital in-formation infrastructure, and laid a foundation for the digital economy to drive high-quality economic development. The digital economy can promote the development of a low-carbon economy by promoting industrial restructuring, transforming the mode of economic growth. First, the development of the digital economy will have a direct impact on energy consumption through different channels such as residents' life, enterprise production, and government regulation, thereby reducing carbon dioxide emissions [9]. Second, data, as an important factor of production, promotes the integration of the digital economy and traditional production factor resources to promote the upgrading of the industrial structure. In the process of the digital economy promoting the rationalization and up-grading of the industrial structure, the energy dependence of the industrial-based secondary industry will be greatly reduced. The industrial structure is upgraded to high-tech industries with low energy consumption and zero pollution, thereby effectively reducing carbon emissions [10]. Third, technological innovation plays an important role in reducing energy consumption and improving energy efficiency [11]. Based on the penetration of industrial Internet, cloud computing and other technologies, real-time dynamic monitoring of energy consumption and pollutant emissions in enterprise production activities to improve energy conservation and emission reduction capabilities.

Therefore, under the background that the development of the digital economy widely affects the sustainable development of China's economy and society, this article will discuss the following questions: What is the relationship between the development of China's digital economy and carbon emissions? How does the development of the digital economy affect carbon emissions? Does the development of the digital economy have a spatial spillover effect on carbon emissions? Are the effects the same across regions? The remaining paper is organized as follows: an analysis and a summary of the relevant literature are presented in Section 2. Measurement of digital economy and carbon emission, and spatial econometric model construction are provided in Section 3. The empirical analysis of spatial spillover effects of digital economy on carbon emissions is illustrated in Section 4. Conclusions and suggestions are presented in Section 5.

2. Literature Review

2.1. Carbon Emission Related Research

Promoting effective energy conservation, emission reduction and low-carbon transformation and development is the inevitable choice to actively respond to climate change, and the key to practice ecological civilization construction. With the increasingly prominent global environmental problems, carbon emission has gradually become a research hotspot in academic circles. At present, the research mainly focuses on the measurement of carbon emission level and the influencing factors of carbon emission.

Scholars mainly use input-output method, life cycle method and total energy consumption method to measure carbon emission level. With regard to the input-output method, Wassily W. Leontief (2000) first introduced the input-output analysis method in economics into the calculation of carbon emission level [12]. Su et al. (2017) analyzed Singapore's carbon emissions from the perspective of demand by using I-O method, and found that the direct emissions of high-income families increased the most, while the implied emissions of middle-income families increased the most [13]. Regarding the life cycle method, Shang and Geng (2021) established a carbon emission calculation model based on the whole life cycle assessment, and measured the carbon emission of residential buildings [14]. Li Yu et al. (2022) calculated the carbon emissions of dairy industry from 2008 to 2020 based on the whole industrial chain, and found that grassland carbon sink can effectively neutralize carbon emissions [15]. With regard to the total energy consumption method, Zhang Mei et al. (2019) estimated the provincial carbon emissions from three aspects: energy consumption, industrial material consumption and waste discharge with the help of statistical data of crude oil, raw coal, natural gas and steel bars [16]. Shi et al. (2019) calculated China's carbon dioxide emissions based on coal, coke, crude oil, gasoline, kerosene, diesel oil, fuel oil and natural gas, and found that it has multi-dimensional spatial-temporal hierarchy, and the emission reduction strategy adapted to local conditions is beneficial to the Chinese government's emission reduction [17].

As for the influencing factors of carbon emissions, the literatures have used LMDI factor decomposition method to study the influence of energy type, structure and in-tensity on carbon emissions (Obas et al., 2006; Bhattacharyya et al., 2010; Simone et al., 2011; Zhang et al., 2019) [18-21], and some scholars have found that population growth is the main factor affecting carbon emissions (Sanglimsuwan, 2012; Chontana-wat, 2019) [22, 23]. In addition, Manta et al. (2020) used FMOLS method and VECM model to study the relationship between carbon emissions and economic growth and financial development in 10 Central and Eastern European countries, and found that there is a two-way causal relationship [24]. Song et al. (2021) used the bi-level stochastic frontier model to analyze the opposite bilateral effects of FDI on carbon emission performance [25]. Furthermore, FDI can affect energy intensity and then carbon emission (Wang et al., 2021) [26]. Jin et al. (2022) found that the change of solar radiation affects the global carbon cycle by influencing the climate through scenario simulation [27].

To sum up, the academic research on carbon emissions has formed relatively mature research results, and a lot of research has been carried out on the measurement of carbon dioxide emissions. However, at present, a unified measurement method has not been formed, the time span is short, the years are discontinuous, and there is no re-search on the latest changes.

2.2. Research on Digital Economy

Digital economy has become a new engine of high-quality development. Grasp the opportunities of digital economy development, and then seize the commanding heights of future development. Since Tapscoot (1996), the "father of digital economy", put for-ward digital economy [28], countries all over the world have carried out extensive re-search on digital economy from both qualitative and quantitative perspectives.

This paper defines the definition of the digital economy, and analyzes the development trends and promotion policies of the digital economy. Aguila et al. (2003) divided the digital economy into four dimensions: infrastructure, e-commerce, software programs and intermediaries from two levels of goods and services [29]. Watanabe et al. (2018) put forward a new view-point of digital economy measurement, introducing GDP into digital economy and interpreting it as uncaptured GDP [30]. As a new economic form (Pei et al., 2018)[31], the essence of digital economy is the real economy of digital technology (Xie et al., 2022) [32]. Building an information service platform can maximize the advantages of the digital economy (Xu et al., 2020) [33].

Based on the perspective of quantitative analysis, scholars' research on statistics and measurement of digital economy is relatively mature. Chen et al. (2022) formulated a digital economic accounting framework based on four dimensions: data and information infrastructure, urban services, urban government and industrial economy [34]. Chen et al. (2022) divided digital economy into basic sector, integration sector and alternative sector, and comprehensively analyzed the structure and contribution of digital economy [35]. With the rapid development of digital economy, scholars gradually began to study the impact of digital economy development on industrial structure optimization (Su et al., 2021) [36], urbanization construction (Chen et al., 2022) [37] and green growth (Ren et al., 2022) [38] with the help of panel data model and Spatial Dubin Model. Focusing on the social effects of digital economy, the linkage between green economy and digital economy contributes to the coordinated development of urban economy and the improvement of people's sense of well-being, thus promoting the elimination of urban polarization and the gradual realization of sustainable development (Savchenko 2020) [39].

To sum up, the definitions of the digital economy in the academic world are not uniform, and they mostly use a single-angle indicator system or separate statistical indicators to measure, resulting in differences in measurement results. Moreover, the indicator system constructed from a single perspective is difficult to objectively and comprehensively reflect the development of the digital economy, which is not conducive to the formulation of industrial policies and standards.

2.3. Research on the Impact of Digital Economy on Carbon Emissions

The environmental improvement effect of digital economy is one of the focuses of academic circles. For example, as an environment-friendly industry in digital economy (Yang et al., 2021) [40], the Internet industry itself can squeeze the development space of industries with high energy consumption and high emissions through crowding out effect, which has a direct or indirect impact on carbon emissions, thus promoting green and high-quality development.

Haseeb et al. (2019) found that Internet use and mobile cellular subscription have significant adverse effects on carbon dioxide emissions, while communication technology has made positive contributions to reducing carbon emissions [41]. Ulucak and Khan (2020), based on the panel data of BRICS countries from 1990 to 2015, found that the use of information and communication technology can reduce carbon dioxide emissions by promoting technological upgrading in various economic sectors [42]. Ujabal et al. (2021) studied the impact of ICT and foreign direct investment on environmental pollution in major Asia-Pacific countries from 1990 to 2018, and found that ICT and foreign direct investment had a negative impact on carbon emissions or environmental pollution [43]. On the other hand, Shobande (2021), using Mundlak and Hausman-Taylor methods and the feasible generalized least square method, found that the increase of Internet penetration has a positive temporary impact on the environment, and the temporary change of ICT usage will increase carbon emissions, while in the long run, ICT usage can reduce carbon emissions [44]. Xu (2022) selected the data of 286 prefecture-level cities, used spatial econometric model and spatial double difference model to study and found that the digital economy has a significant negative impact on carbon emissions [45].

To sum up, although academic circles have conducted extensive and in-depth discussions on the environmental improvement effect of digital economy, which pro-vides some theoretical support for explaining the effect of digital economy on carbon emissions, the above studies still fail to provide reliable evidence for the effect of digital economy on carbon emissions. On the one hand, the theoretical discussion of the effect of digital economy on carbon emissions in existing studies is still insufficient. On the other hand, the empirical test of the effect of digital economy on carbon emissions also needs to be improved.

3. Method and Data

3.1. Spatial Econometric Model

3.1.1. Spatial Correlation

In the first place, spatial correlation of variables is tested to judge the applicability of spatial econometric model. Generally, the global Moran's I index is used in the test, and is calculated as

$$Moran's\ I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n}W_{ij}(Y_i-\bar{Y})(Y_j-\bar{Y})}{\sum_{i=1}^{n}\sum_{j=1}^{n}W_{ij}\sum_{i=1}^{n}(Y_i-\bar{Y})^2} \tag{1}$$

where n is the number of units studied, W_{ij} is the spatial weight matrix,

3.1.2. Spatial Weight Matrix

Describing the correlation between two objectives, spatial weight matrix has various construction forms, which are mainly divided into adjacency matrices and distance matrices. Further, the distance matrix can be established based on economic distance or geographical distance. In view of the multicollinearity problem of the matrix established based on economic distance, this paper selects the matrix established based on geo-graphical distance:

$$\begin{cases} w_{ij}=\dfrac{1}{d_{ij}^2} \\ d_{ij}=\arccos[(\sin\phi_i\times\sin\phi_j)+(\cos\phi_i\times\cos\phi_j\times\cos(\Delta\tau))]\times R \end{cases} \tag{2}$$

where ϕ_i and ϕ_j represent the latitude and longitude of the geometric center of an area, $\Delta\tau$ is the longitude difference and R is earth radius.

3.1.3. Spatial Econometric Model

Among all spatial econometric models, Spatial Lag Model (SLM), Spatial Error Model (SEM) and Spatial Dobbin Model (SDM) are the most commonly applied.

Spatial Lag Model (SLM) is often used to explore the impact of the research object in a certain place on that in the adjacent area. The impact of the spatial lag factor of the research object is considered in the model, and the model is expressed as:

$$Y = \rho WY + X\beta + \mu,\ \mu \sim (0, \delta^2 I) \tag{3}$$

where W is the spatial weight matrix; Y and X represent explained and independent variables separately; β is the parameter vector; μ is the vector of random error terms; ρ is the spatial coefficient, which indicates the influence of spatial lag WY on Y.

Inter Error Model (SEM) reflects the spatial dependence through the error term. The model formula is as follow.

$$Y = \lambda Wy + X\beta + WX\delta + \varepsilon,\ \varepsilon \sim (0, \delta^2 I) \tag{4}$$

In the above formula, W is the spatial weight matrix and λ is the spatial error correlation coefficient, which represents the spatial dependence of perturbation terms. This model indicates that the missing variables also have spatial correlation.

Spatial Dobbin Model (SDM) describes the spatial substantive correlation and disturbance correlation, and considers the spatial lag factor. In addition to the interaction between independent variables X of different regions, the model also includes the influence of independent variables X of a region on dependent variables Y of adjacent regions. The model is generally constructed as

$$Y = \lambda Wy + X\beta + WX\delta + \varepsilon,\ \varepsilon \sim (0, \delta^2 I) \tag{5}$$

where $WX\delta$ is the influence of independent variables X from adjacent areas, and δ is the corresponding coefficient variables.

3.2. Characteristics of Core Variables

3.2.1. Spatiotemporal Evolution Characteristics of the Development of China's Digital Economy

(1) Measurement of development level of digital economy

Based on the connotation of digital economy and the requirements of subsequent research on the impact effect of carbon emissions, considering the difficulty of data acquisition, and following the scientific and representative principles of the index system, this paper establishes a comprehensive evaluation index system of the development level of digital economy, including four secondary indicators and 15 tertiary indicators of digital infrastructure, digital industry, digital governance ability and digital Inclusive Finance. In order to make the indicators of different regions comparable in time section, the article tries to choose the proportional indicators. The data used in the calculation process are from the China Statistical Yearbook, China Statistical Yearbook on Science and Technology and China Academy of Information and Communication Technology. Digital Inclusive Finance is represented by the index compiled by Guo Feng et al. (2020). The detailed indicators are shown in Table 1.

Table 1. *Digital economy development level index system of China.*

Ⅰ level	Ⅱ level	Ⅲ level
Digital economy development level	Digital infrastructure	Internet penetration rate (%)
		Mobile phone penetration rate (1/100 people)
		Optical cable line density (km/km^2)
		Number of internet access port (10,000)
	Digital industry development	Proportion of computer and software employees (%)
		Per capita Telecom traffic (Yuan/person)
		High tech R&D capital stock (10,000)
		Online mobile payment level (index)
	Digital governance capability	Proportion of internal expenditure of R&D funds (%)
		Per capita fiscal expenditure on science and technology (Yuan/person)
		Average years of Education (year)
		Per capita technology contract transaction volume (Yuan/person)
	Digital Inclusive Finance	Coverage of digital Finance (index)
		Depth of digital financial coverage (index)
		Digitalization degree of digital Finance (index)

When determining the weight of the index system, considering that the subjective weighting method may be affected by human factors, resulting in bias in determining the index weight, the objective weighting method is used for calculation. The entropy weight method can reflect the utilization value of the index information entropy, and has high reliability and accuracy. This paper uses the entropy weight method to weight the indicators in Table 1 to obtain the national digital economy development level from 2011 to 2019.

(2) The time evolution of the development level of the digital economy

Figure 2 shows the trend chart of the development level of digital economy in 30 provinces in China from 2011 to 2019. As can be seen from the figure, all 30 provinces in China have shown a roughly similar upward trend in the level of digital economic development, and most provinces have grown faster in recent years than in early 2011, such as Tianjin (2), Fujian (13), Guizhou (24), etc. The growth rate of each province in the past nine years is basically the same, such as Jiangsu (10), Shandong (15) and Hubei (17). It can also be found that the development level of digital economy in Beijing (1) and Guangdong (19) is significantly higher than that in other provinces, followed by Shanghai (9), Jiangsu (10) and Zhejiang (11).

(3) Spatial evolution of the development level of digital economy

Although the digital economy in all provinces and province-level municipalities has developed, there are regional differences in the improvement of development speed and quality, especially between the East and West. Judging from the results in Table 2, the spatial development of the digital economy presents obvious regional imbalances. From 2011 to 2019, China's digital economy was mainly concentrated in the economically developed eastern region. The digital infrastructure was relatively complete, the talent pool was abundant, and the level of innovation and digital technology application was high, providing a good environment for the development of the digital economy. Although the central region started late, it has a strong development momentum and a high level of digital infrastructure. The innovation ability and technology application level in the western region are relatively backward, the infrastructure of digital economy development needs further improvement, and the development level of digital economy is lower than that of the eastern and central regions. However, with the vigorous promotion of regional coordinated development and the implementation of a series of western development policies such as "East and West", the development level of the digital economy in the western region is rapidly improving.

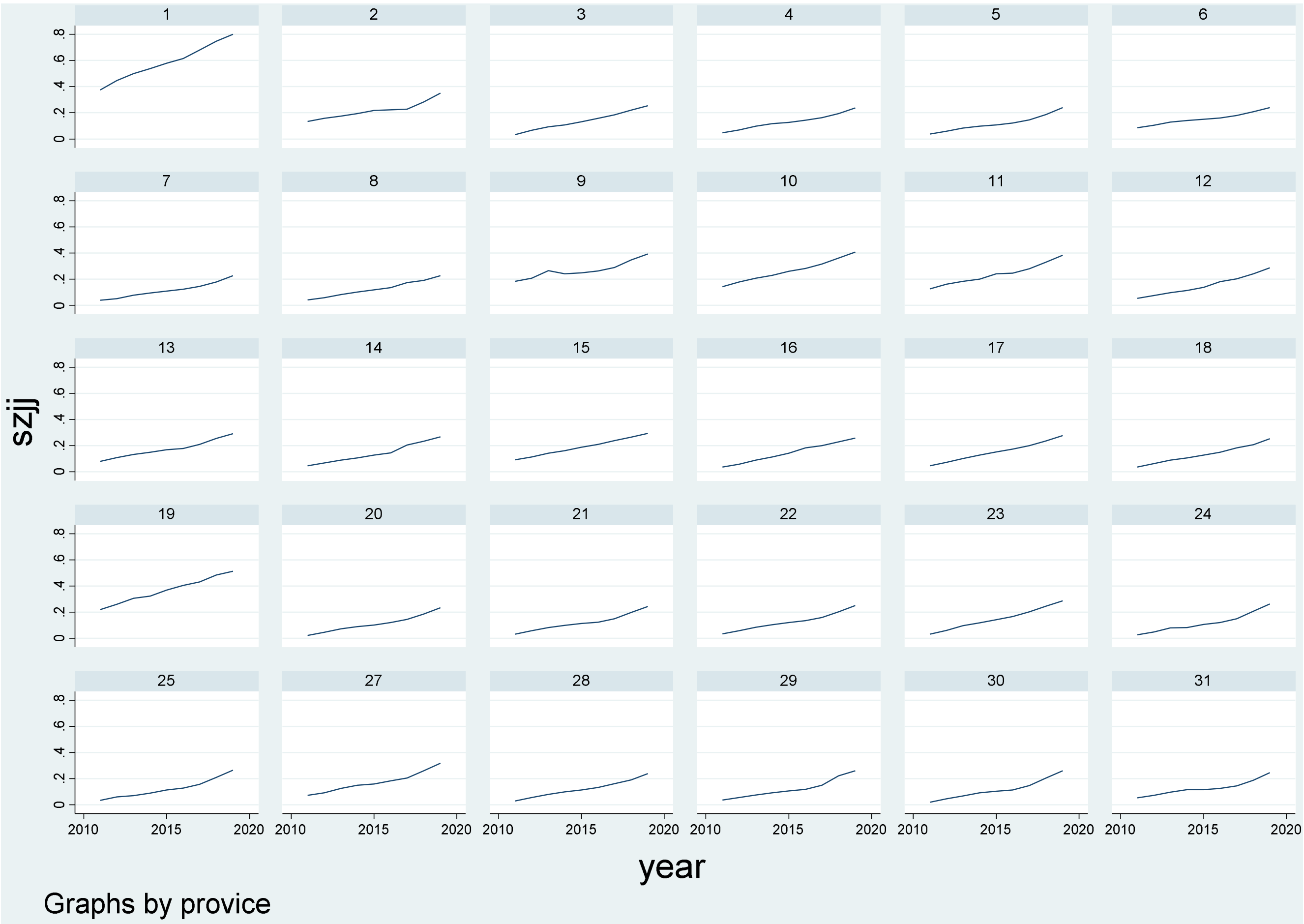

Figure 2. Trend of provincial digital economy development level from 2011 to 2019.

Table 2. Development level of digital economy in three regions of China.

Year	2011	2012	2013	2014	2015	2016	2017	2018	2019
Eastern region	0.137	0.1698	0.2021	0.2169	0.243	0.2607	0.2896	0.3368	0.3797
Central region	0.0437	0.0651	0.0913	0.1107	0.1307	0.1545	0.1846	0.2148	0.255
Western region	0.0363	0.0598	0.0852	0.1024	0.1171	0.1332	0.1612	0.2095	0.2605

In order to further intuitively analyze the development level of China's digital economy, this paper draws a spatial distribution map of the development level of digital economy in China's provinces and cities in 2011, 2014, 2017 and 2019. Set the values for Tibet, Hong Kong, Macau, Taiwan to 0 due to lack of data. It can be seen from Figure 3 that the development of China's digital economy has the characteristics of geographical and spatial aggregation. From 2011 to 2019, it has concentrated to the eastern coast and then to the economically developed regions such as central and southern China, showing an obvious aggregation trend. In 2011, the development of digital economy was mainly concentrated in Beijing, Tianjin, Guangdong, Jiangsu, Zhejiang and other regions. In 2014, it was mainly concentrated in Beijing, Zhejiang, Shandong, Jiangsu, Guangdong and other regions. In 2017, it was mainly concentrated in Beijing, Zhejiang, Shandong, Jiangsu, Guangdong, Fujian, Anhui, Jiangxi and other regions. In 2019, the development of digital economy was further concentrated in the southeast. In previous years, the provinces with high level of digital economy development were still in the leading position, while The Pearl River Delta, Yangtze River Delta and Beijing, Tianjin and Hebei have played a significant driving role in the surrounding areas.

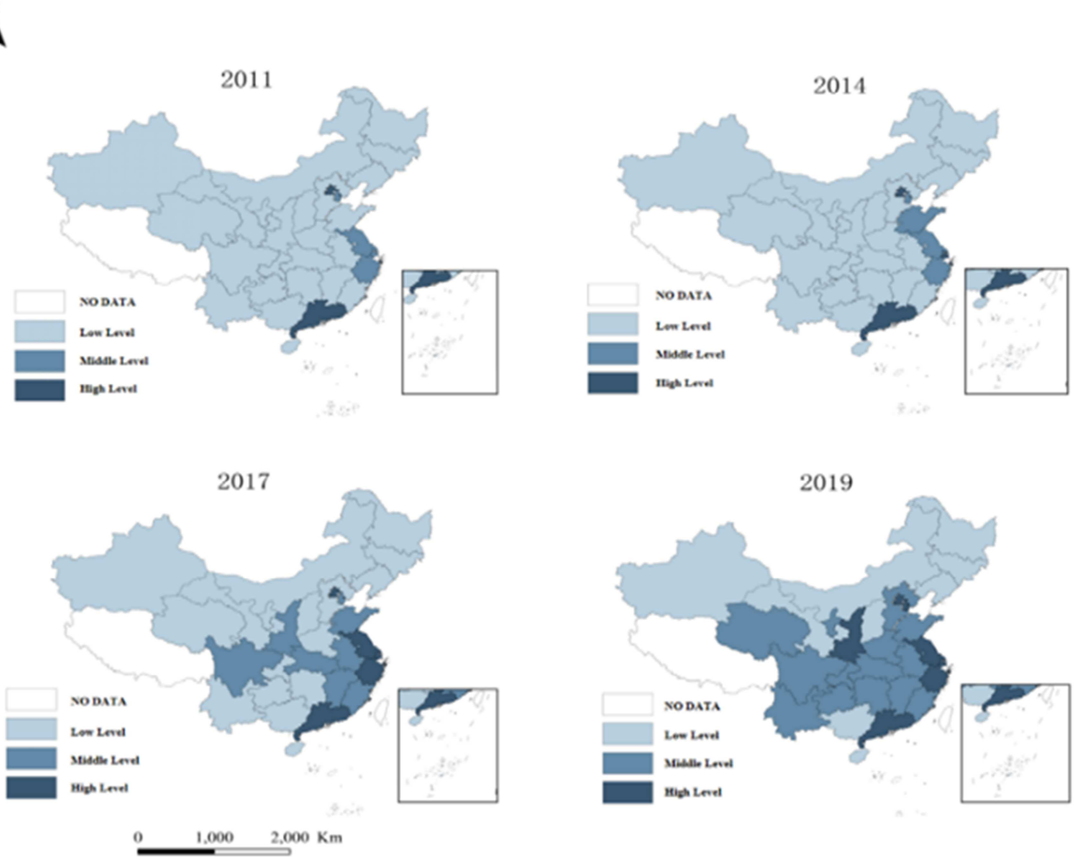

Figure 3. *Spatial distribution of provincial digital economy development level from 2011 to 2019.*

3.2.2. Spatiotemporal Evolution of Carbon Emissions

(1) Measurement of China's carbon emission level

In recent years, frequent natural disasters and extreme weather events have drawn people's attention to the urgent issue of global warming, and the environmental issue of carbon emissions has increasingly become the focus of domestic and foreign scholars. The premise of studying carbon emission is to determine the calculation method of it. Considering that carbon dioxide and other greenhouse gases mainly come from the combustion of fossil energy, most scholars in China chose energy consumption to measure carbon emissions. By combing the literature, referring to a relatively mature carbon emission accounting method introduced in the IPCC greenhouse gas guide, this paper uses the consumption of a variety of fossil fuels to estimate the national and provincial carbon emissions, and then the conversion coefficient is applied to convert the carbon emissions into carbon dioxide emissions. The specific formula is:

$$C_{co_2} = k \cdot \sum_{i=1}^{n} E_i \cdot \delta_i \tag{6}$$

In the above formula, C_{co_2} is carbon emissions; k conversion factor ($k = 44/12$); E_i is the consumption of the i^{th} fossil fuel; δ_i is the carbon emission coefficient of the i^{th} fossil fuel. δ_i can be obtained as:

$$\begin{aligned}&\text{Carbon emission coefficient} = \text{Default carbon oxidation}\\&\times \text{Default carbon content}\\&\times \text{Average low calorific value}\end{aligned}$$

Parameters in the above formula of different kinds of fossil fuels are shown in Table 3.

Table 3. *Carbon emission factors of different fossil fuels.*

Fossil fuels	Average low calorific value (KJ/kg/m)	Default carbon content (kgC/CJ)	Default carbon oxidation rate	Carbon emission coefficient (tC/t)
coal	20908	25.8	1	0.53943
coke	28435	29.2	1	0.83030
crude oil	41816	20	1	0.83632
gasoline	43070	18.9	1	0.81402
kerosene	43070	19.6	1	0.84417
diesel oil	42652	20.2	1	0.86157
fuel oil	41816	21.1	1	0.88232
natural gas	38931	15.3	1	0.59564
liquefied petroleum gas	50179	17.2	1	0.83632

The fossil fuel consumption data is collected from the China Statistical Yearbook and China Energy Statistical Yearbook over the years. Since that the data of Tibet, Hong Kong, Macao and Taiwan are seriously missing, so this paper excludes them and selects the data of other 30 provinces as the research sample. For the estimation of national carbon emissions, in view of the fact that China's energy consumption is divided into three categories in statistics: coal, oil and natural gas, this paper only selects the carbon emissions of these three fossil fuels to measure the national carbon emissions; For the provincial carbon emissions, although there are 11 types of energy according to the statistics of each province, due to the serious lack of data of liquefied petroleum gas and oil in each province before 2013, and the possibility of double calculation of electric power as a secondary energy in the calculation of energy consumption, under all aspects of comprehensive consideration, this paper finally selects 8 kinds of fossil energy such as coal, crude oil, kerosene and natural gas to calculate the provincial carbon emissions.

In addition, in order to measure the relationship between economic growth and carbon emissions, this paper also calculates the carbon emission intensity, i.e., the ratio of carbon emissions to real GDP is used to measure the amount of carbon dioxide emitted per unit of economic output. The real GDP is calculated based on 2011.

(2) Temporal evolution of carbon emission

As can be seen from Figure 4, the carbon emissions in each province shows different upward and downward trends. Carbon emissions in some provinces remain at a relatively stable level, such as Shanghai (9), Henan (21) and Qinghai (28). Most provinces show a fluctuating upward trend, such as Shanxi (4), Inner Mongolia (5), Jiangsu (10), Shandong (15), Xinjiang (30), and a few provinces show a downward trend, such as Beijing (1). In addition, due to the promotion of low-carbon and emission reduction policies in recent years, carbon emissions in some provinces have decreased slightly, say Jilin (7), Henan (16), Sichuan (23) and Yunnan (25).

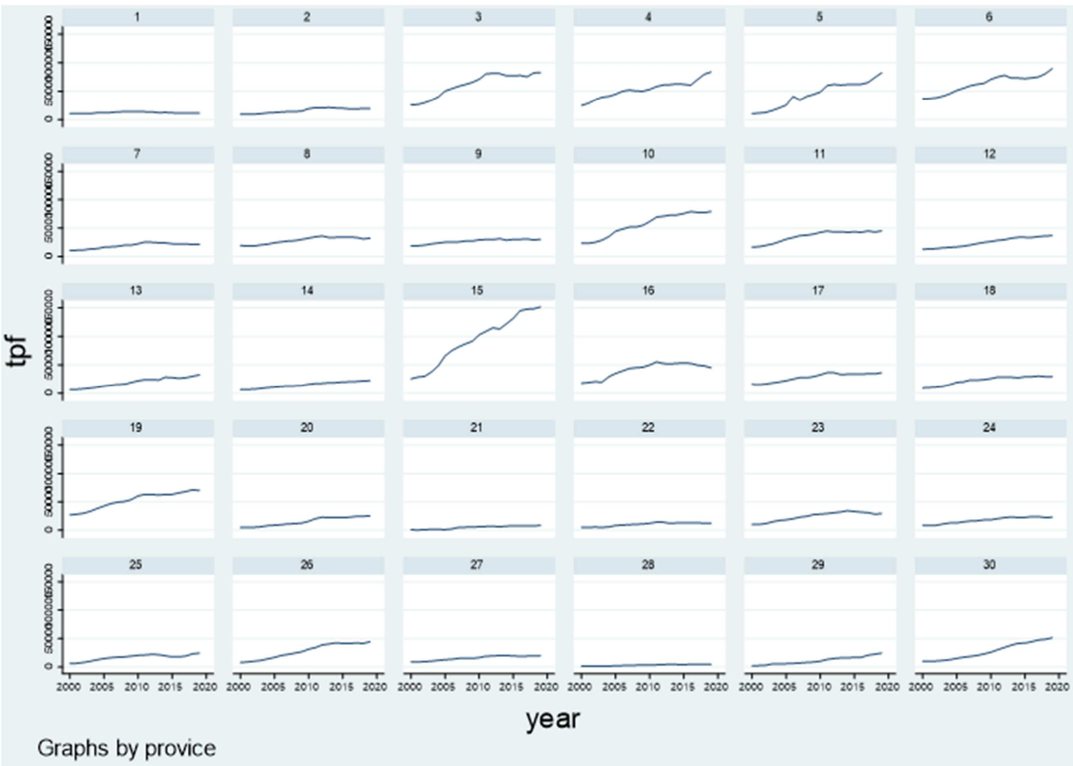

Figure 4. *Trend of total carbon emissions of 30 provinces in China from 2000 to 2019.*

(3) Spatial evolution of carbon emissions

According to the result in table 4, the spatial development of China's carbon dioxide emissions shows significant geographical imbalance. From 2000 to 2019, China's carbon dioxide emissions are mainly concentrated in the eastern region, which accounts for about half of China's total carbon emissions. Most of the relatively economically developed eastern regions have high carbon emissions, mainly because these regions have a high degree of industrialization, leading to large corresponding energy consumption. The carbon emissions of the central and western regions account for a low proportion of the country. Before 2010, due to the slow economic development and the large population and multiple industries in the central region, the carbon emissions of the central region are higher than those of the western region. After 2010, due to the vigorous development of the western region by the state, opportunities for rapid development have been brought to western economy, resulting in the gradual increase of carbon emissions of energy consumption.

Table 4. *Carbon dioxide emissions in the east, central and western regions of China from 2000 to 2019.*

Year	Eastern region	Central region	Western region
2011	416340.0	223942.8	267443.8
2012	424247.8	225605.5	287330.5
2013	422445.8	225331.7	293476.9
2014	431110.1	229022.8	300132.2
2015	444205.8	231635.9	295777.9
2016	460745.6	229932.7	299997.6
2017	463866.6	240457.5	312780.2
2018	475023.3	249407.4	323067.2
2019	483979.8	253189.9	342782.2

In order to further visually analyze China's carbon dioxide emission level, this paper draws the spatial distribution map of carbon emission levels of provinces and province-level municipalities in China in 2011, 2014, 2017 and 2019. Due to the lack of data, the values of Tibet, Hong Kong, Macao and Taiwan are set to 0.

As can be seen from Figure 5, China's carbon emissions have the characteristics of geographic and spatial agglomeration. Eastern coast and other economically developed areas, especially provinces with industries as the main industries, are the main concentration of carbon emissions. In 2011, China's carbon emissions were mainly concentrated in Liaoning, Hebei, Shandong provinces and so on, and in 2014 and 2017, they were mainly concentrated in Inner Mongolia, Shanxi, Liaoning, Hebei, Shandong, Jiangsu, Guangdong and other regions. In 2019, the carbon emission level further concentrated in the southeast, and Shanxi, Liaoning, Shandong and Guangdong are still high carbon emission amplification provinces. Compared with 2014, the spatial distribution of carbon emission in 2017 and 2019 didn't change significantly, which may be due to the small span of years in the research. In addition, energy consumption and carbon emission levels have changed slowly over the years with the implementation of low-carbon policies.

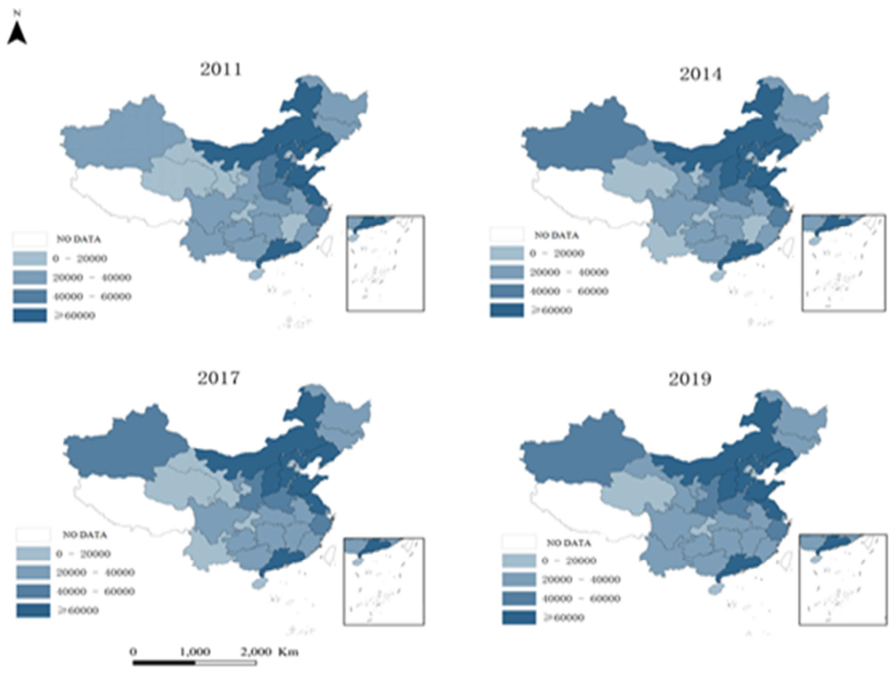

Figure 5. *Spatial distribution of provincial carbon emissions from 2011 to 2019.*

3.3. Model Variable Selection and Data Sources

3.3.1. Model Variable Selection

In order to explore the impact of the development of digital economy on carbon emissions, the following variables are used to construct the model:

Explained variable: carbon emission (recorded as tpf). According to the consumption of eight common fossil fuels, the carbon dioxide emission is obtained by conversion.

Explanatory variable: digital economy development level index (recoded as dig). According to the established evaluation index system, the development level of digital economy is measured from four aspects, and the development level index of digital economy is calculated by entropy weight-TOPSIS method.

Control variables: in order to control the impact of other factors on the development of digital economy, referring to the research done in previous studies, this paper mainly selects five control variables to represent the level of economic development (gdp), urbanization (city), opening to the outside world (open), industrial structure (str) and technological innovation ability (tec). The economic development level is measured by per capita GDP. The urbanization level is measured by the urbanization rate, that is, the proportion of the total urban population in the total population at the end of the year. The improvement of the urbanization rate will lead to the improvement of the ag-glomeration level of economy and population, and then affect the regional carbon emission level. The degree of opening is expressed by the proportion of the total import and export of the region in the region's actual GDP in that year. With the strengthening of the scale of foreign trade, China has introduced foreign industries and technologies, which may also have an impact on carbon emissions to a certain extent. The level of industrial structure is measured by the proportion of the tertiary industry in the secondary industry. Due to different energy consumption, the carbon dioxide produced in the secondary industry is generally higher than that of the tertiary industry, and the optimization of industrial structure is helpful to reduce carbon emissions. Considering the fact that improvement of innovative technologies helps to improve energy efficiency, reduce carbon emissions from the source and promote energy conservation and emission reduction of industrial enterprises, the level of technological innovation is measured by the number of patent applications authorized per 10000 people.

Table 5. *Description of spatial econometric model variables.*

Variable type	Variable symbol	Variable interpretation
Core variable	tpf	Carbon emission (10000 tons)
	dig	Digital economy development level
Control variable	gdp	Economic development level (Yuan / person)
	city	Urbanization level (%)
	open	Opening up level (%)
	str	Industrial structure (%)
	tec	Technological innovation capacity (PCs. / 10000 persons)

3.3.2. Data Sources

This paper selects the panel data of 30 provinces in China except Tibet, Hong Kong, Macao and Taiwan from 2011 to 2019. All the original data are collected from China Statistical Yearbook, China Statistical Yearbook on Science and Technology, China Statistical Yearbook on Environment, provincial statistical communiques and statistical yearbooks, and the research reports on digital economy, Internet and e-commerce is-sued by national institutions.

In order to eliminate the influence of heteroscedasticity, this paper do logarithm treatment on the explained and control variables, while the explanatory variable is not logarithmic.

4. Results and Discussion

4.1. Spatial Autocorrelation Test of Carbon Emissions

First, by calculating the global Moran's I index to examine the spatial correlation of carbon emissions and verify the spatial agglomeration performance of China's carbon emissions. The results are shown in Table 6.

According to Table 6, it can be seen that the global Moran's I index of carbon emissions from 2011 to 2019 are all positive values, and they all show significance at the 5% level. This shows that China's carbon dioxide emissions show a positive spatial correlation between regions, with the characteristics of spatial agglomeration. The regions with more carbon dioxide emissions tend to be close to other regions with relatively high emissions, while the regions with less carbon dioxide emissions tend to be close to other regions with relatively low emissions. This fully shows that the impact caused by regional differences should be considered in the following analysis and re-search process.

Table 6. *The global Moran's I index of China's regional carbon emissions from 2011 to 2019.*

Time	Moran's I	Variance	Z value	P value
2011	0.156	0.095	2.004	0.045
2012	0.155	0.095	2.006	0.045
2013	0.167	0.095	2.130	0.033
2014	0.165	0.095	2.096	0.036
2015	0.153	0.094	1.989	0.047
2016	0.156	0.095	2.017	0.044
2017	0.159	0.095	2.034	0.042
2018	0.173	0.094	2.200	0.028
2019	0.167	0.095	2.128	0.033

From the perspective of time trend, the global Moran's I index of China's carbon dioxide emissions shows a trend of increasing volatility. The Moran's I value of global carbon emissions is between 0.153-0.173. The Moran's I index was at its smallest in 2015 and peaked in 2018. The change of Moran's I index shows that with the development of economy and society and the improvement of people's living standards, the connection between regions is getting closer and closer, the industrial development between regions is also affecting each other, and the independence between regions is gradually weakening, resulting in Spatial effects of inter-carbon emissions.

In order to study the local spatial correlation of carbon emissions in China, Moran's I scatter plot is drawn to analyze the spatial correlation patterns of various provinces and cities. This paper will use the Moran's I scatter plot in 2011, 2014, 2017, and 2019 to analyze, and the results are shown in Figure 6.

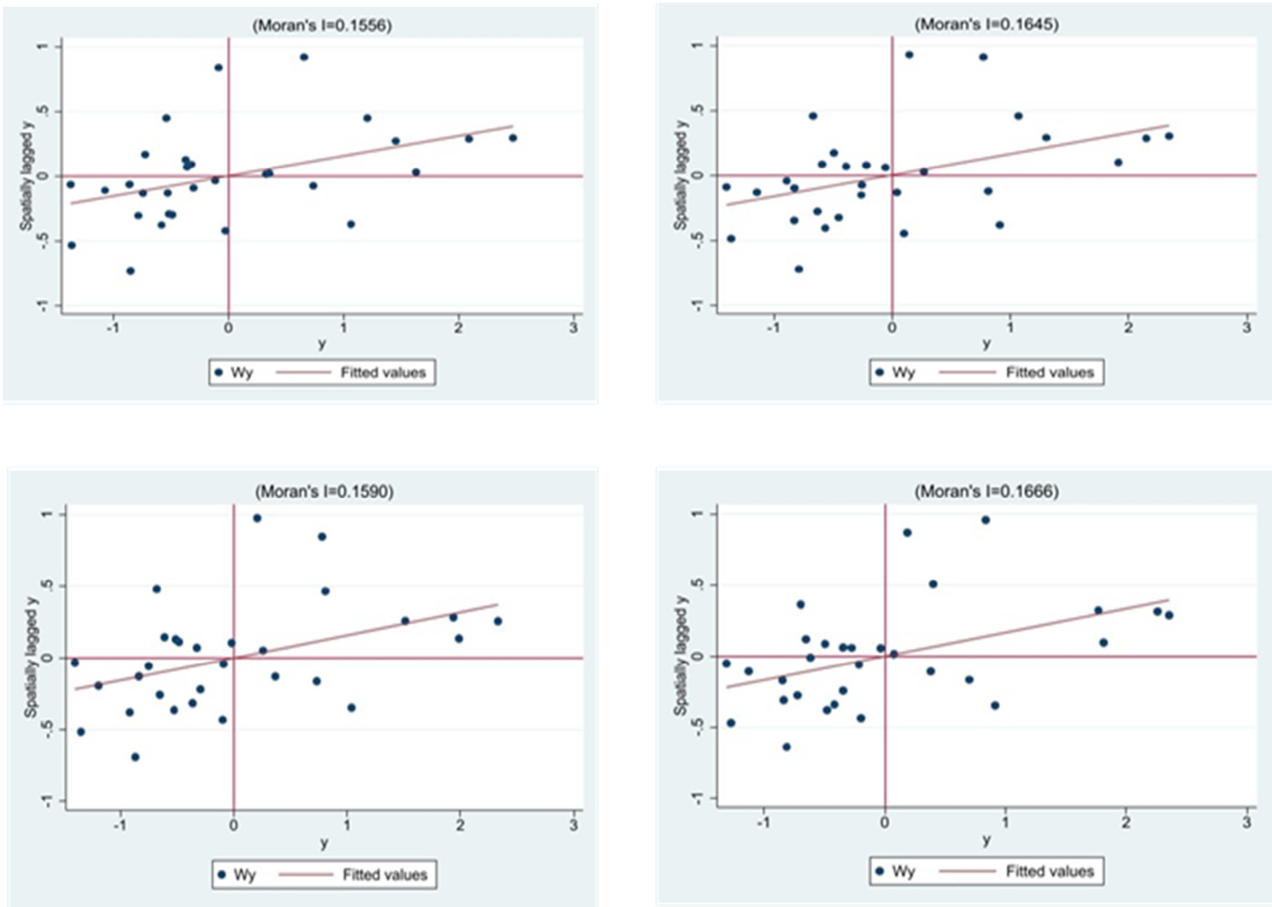

Figure 6. *Moran's I scatter plot of China's carbon emission levels in 2011, 2014, 2017 and 2019.*

Figure 6 shows the Moran's I scatter plot of carbon emissions in 30 provinces and cities in China in 2011, 2014, 2017, and 2019. It can be seen that the scatter points of Moran's I index are evenly distributed among the four quadrants, among which the first quadrant H-H is the high carbon emission-high aggregation area; the second quadrant L-H is the low carbon emission-high aggregation area; the third quadrant L-L is the low carbon emission-low aggregation area; the fourth quadrant H-L is the high carbon emission-low aggregation area. In 2011, 22 provinces showed positive spatial correlation, of which 8 provinces are located in the first quadrant and 14 are located in the third quadrant, and the spatial heterogeneity is strong; in 2014, 2017 and 2019, 70% of the regions shows positive spatial correlation, of which 8 provinces are in the first quadrant, 13 provinces are in the third quadrant, 6 provinces are low carbon emission-high aggregation area, and 3 provinces are high carbon emission-low aggregation area.

4.2. Research on the Adaptability of Carbon Emission Spatial Models

The spatial correlation test of carbon emissions shows that China's carbon emissions have a positive spatial correlation. Therefore, when studying the relationship between the development of the digital economy and carbon emissions, the spatial effect cannot be ignored. The explanatory variable selected in this chapter is carbon emission (lntpf), the core explanatory variable is the level of digital economy development (dig), and the control variables are the level of economic development (lngdp), urbanization level (lncity), level of opening (lnopen), industrial structure (lnstr), tech-nological innovation capability (lntec).

In this paper, Hausman test, LR test, LM test and Wald test are used to determine the specific form of the spatial econometric model. The test results are shown in Table 7.

Table 7. *The global Moran's I index of China's regional carbon emissions from 2011 to 2019.*

Test methods		Statistic	P
Hausman test	Random test	22.97	0.001
LR-test	Space fixed effect	39.27	0.001
	Time fixed effect	57.68	0.001
LM test	LM test no spatial lag	10.145	0.001
	Robust LM test no spatial lag	5.381	0.02
	LM test no spatial error	7.894	0.005
	Robust LM test no spatial error	14.562	0.001
Wald test	Spatial lag	12.67	0.0486
	Spatial error	13.08	0.0418

4.3. Analysis of Spatial Econometric Empirical Results

The assumption of the spatial econometric model is that when the lag effect coefficient is not greater than 1, the lag model can be stable. Table 8 shows the empirical results of the SDM, SLM and SEM models. It can be seen that the spatial autoregressive coefficient (rho) of the SLM model is 0.171, which is smaller than 1, which indicates that the SLM model is relatively robust. At the same time, by comparing the Log-likelihood of the three models, it can be seen that since the Log-likelihood of the Spatial Lag Model (344.536) and the Spatial Error Model (344.155) are both smaller than those of the Spatial Doberman Model (350.820), it is considered more effective to establish an SDM model. And because at the 5% significant level, the null hypothesis that the SDM model is simplified to the SLM model and the SEM model is rejected. In addition, when the SLM model and the SEM model are used to carry out the analysis, the spatial effect of the independent variables in the study region and its adjacent regions are not considered, which further verifies the optimality of the double fixed SDM model established in the paper for empirical research.

Table 8. *Calculation results of spatial econometric model.*

Explanatory variables	SDM		SLM		SEM	
	Coefficient	Z	Coefficient	Z	Coefficient	Z
dig	-0.825***	-2.92	-0.845***	-3.28	-0.830***	-3.27
lngdp	-0.934***	-4.61	-0.708***	-3.97	-0.731***	-4.00
lncity	0.492**	2.35	0.658***	3.49	0.680***	3.57
lnopen	0.010	0.35	0.007	0.26	0.005	0.18
lnstr	-0.132**	-2.01	-0.101*	-1.75	-0.096*	-1.69
lntec	-0.063**	-2.42	-0.050**	-2.04	-0.053**	-2.07
W*dig	-0.245*	-1.86				
W*lngdp	0.657	1.59				
W*lncity	0.360	0.87				
W*lnopen	0.076	0.88				
W*lnstr	-0.113	-0.74				
W*lntec	-0.039	-0.78				
rho	0.197**	2.20	0.171*	1.90		
Log-likelihood	350.820		344.536		344.155	
Direct effect	-0.813***	-2.77				
Indirect effect	-0.168*	-1.81				
Total effect	-0.981***	-2.96				
Spatial fixed	YES		YES		YES	
Time fixed	YES		YES		YES	
Number of samples	270		270		270	

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

4.3.1. Analysis of Influencing Factors

For the core explanatory variables, under the SDM model, the regression coefficient of the digital economy development level (dig) is -0.825, and under the SLM model, the regression coefficient of the digital economy development level (dig) is -0.845. Under the SEM model, the regression coefficient of dig is -0.83, and the three models all pass the 1% significance level, showing negative significance, indicating that the development of the digital economy has a significant negative inhibitory effect on carbon emissions in their respective regions. According to the test results of the Space Durbin model, for every 1% increase in the development level of the digital economy, carbon emissions will decrease by 0.825%. The development of the digital economy plays an important role in energy conservation and emission reduction, and carbon emissions can be reduced in various ways: 1) The development of the digital economy has led some enterprises to actively look for ways to adjust and upgrade their industrial structure, and use the Internet platform to promote the research and development of products or services. In particular, the emergence and development of e-commerce, the promotion of online customization of products, and the promotion of paperless office have all reduced energy consumption to a certain extent. 2) The development of the digital economy has brought many new technologies, and big data has become the most important factor of production. With the further advancement of various smart cities and remote sensing technologies, the combination of the air quality monitoring and early warning platform and the Internet enables people to monitor changes in environmental levels anytime and anywhere, and share data in real time, thereby improving the supervision of air quality and the monitoring of enterprises with excessive carbon emissions. 3) The development of the digital economy has provided a relatively open space for everyone. The role of public opinion can be used to promote some positive environmental behaviors, criticize some behaviors that damage the environment, enhance the public's sense of social responsibility, let people naturally carry out low-carbon activities, and monitor behaviors that pollute the environment anytime, anywhere.

For the control variable, the coefficient of the level of economic development (lngdp) is -0.934, which passes the test at the 1% significance level. For every 1% increase in economic development, carbon emissions will decrease by 0.934%. China's economic development model is changing to a high-quality development stage. Due to the use of clean energy and a series of high-tech applications, the dependence on fossil fuels has weakened, which has inhibited carbon emissions. At the same time, it also shows that China's low-carbon economic development has achieved initial results, and it is necessary to further develop green development and take the road of sustainable development.

The coefficient of urbanization level (lncity) is 0.492, which passes the test at the 5% significance level. For every 1% increase in urbanization level, carbon emissions will increase by 0.492%. With the improvement of urbanization level, the population gradually gathers in cities, and the high level of urban life will bring more travel and increase the demand for energy, which will lead to the increase of carbon emissions.

The coefficient of level of opening (lnopen) is 0.01, but it has not passed the significance test, indicating that level of opening has no significant impact on carbon emissions. Some scholars have found that opening to the outside world can lead to an increase in China's carbon emissions, and used this to verify the hypothesis of a "pollution paradise", while some scholars have found that the vigorous development of China's foreign trade and the continuous optimization of its foreign trade structure have resulted in a continuous increase in the total import and export volume and a continuous improvement in the level of industrial development, which has a positive effect on reducing carbon emissions.

The coefficient (lnstr) of the industrial structure is -0.132, which passes the test at the 5% significance level. For every 1% increase in the industrial structure, carbon emissions decrease by 0.132%. With the transformation of the industrial structure, the heavy industry represented by high energy consumption is gradually transforming into refined light industry. There are fewer resource-intensive enterprises, and the proportion of technology-intensive enterprises is gradually increasing. This will help reduce the burning of fossil fuels and improve production efficiency and production quality, thereby reducing carbon dioxide emissions.

The coefficient of technological innovation level (lntec) is -0.063, which passes the test at the 5% significance level. For every 1% increase in technological innovation level, carbon emissions will correspondingly decrease by 0.063%. The development of high-tech and the improvement of innovation ability will bring low-carbon environmental protection technology, the improvement of enterprise innovation ability will attract the arrival of talents, and the introduction of high-tech will have greater opportunities to optimize production and office methods, reduce energy consumption and carbon dioxide emissions.

4.3.2. Spatial Effect Analysis

From the calculation results in Table 8, it can be seen that the spatial spillover coefficient (rho) of China's carbon emission level is 0.197, and it passes the test at the 5% significance level, which indicates that carbon emission has a significant spatial spill-over effect as a whole, and it is positive the spatial externality. That is to say, the carbon emission level of a certain region is not only affected by various local factors, but also affected by the carbon emission level of adjacent regions, which further verifies that the influence of spatial effects cannot be ignored in the process of empirical research.

From the regression results, the coefficient of W*dig is -0.245, and it passes the test at the 10% significance level, indicating that the development of China's digital economy has a positive externality and has an inhibitory effect on carbon emissions in adjacent regions. Every 1% increase in the level of digital economy development in adjacent re-gions will lead to a decrease of 0.245% in the level of carbon emissions in the region, which reveals the spatial spillover effect of digital economy development on carbon emissions. For the spatial spillover effects of other control variables, the positive spatial spillover effects of lngdp, lncity and lnopen on carbon emissions and the negative spa-tial spillover effects of lnstr and lntec are not significant.

4.3.3. Decomposition of Spatial Spillover Effect of Digital Economy

In order to further explore the spatial effect of the development of the digital economy on China's carbon emissions, the paper decomposes the spatial spillover effect. According to the results in Table 8, the direct effect coefficient of the development of the digital economy on carbon emissions is -0.813, which means that the development of the digital economy in a certain region has a direct reduction effect on carbon dioxide emissions in the region. This effect is generally referred to as a territorial effect, which shows the contribution of the development of the digital economy to the development of a low-carbon economy and the improvement of environmental protection. The indirect effect coefficient of the development of the digital economy on carbon emissions is -0.168, which indicates that the improvement of the level of the digital economy will have an inhibitory effect on the increase of carbon dioxide emissions in adjacent regions. This negative effect is mainly due to the spillover effect between provinces and cities. At the same time, it can be seen that the direct effect of the digital economy is greater than the indirect effect, which shows that the current level of China's digital economy development level has an inhibitory effect on carbon emissions mainly due to the influence of various elements in the region, and the influence of neighboring regions is second.

4.4. Robustness Test

With the gradual expansion of the scale of the digital economy, many domestic commercial institutions have begun to study the digital economy in depth and published the measured digital economy development index. Among them, Caixin Insight is highly authoritative in the research of macroeconomic indexes. The agency cooperates with Brand Big Data (BBD) to formulate an indicator system for the development level of the digital economy from the four parts of digital economy infrastructure, industry, integration, and spillover, and releases the digital economy development index once a month. Many domestic scholars have also conducted a series of studies using this indicator. Therefore, the paper uses the data published by Caixin Insight to re-place the digital economy development index measured in the paper for robustness test.

Table 9. *Regression results of replacing core explanatory variables.*

Explanatory variables	SDM	
	Coefficient	Z value
dig	-0.0664***	-3.12
lngdp	-0.7106***	-3.23
lncity	0.7963***	3.52
lnopen	-0.1148***	-3.60
lnstr	-0.0148	-0.21
lntec	0.0917***	3.23
W*dig	-0.2270**	-2.30
W*lngdp	0.3972	0.68
W*lncity	0.7873	1.39
W*lnopen	-0.0308	-0.34
W*lnstr	-0.2223	-1.31
W*lntec	-0.1443*	-1.93
rho	0.2075**	2.23
Log-likelihood	321.2887	
Direct effect	-0.060**	-2.14
Indirect effect	-0.2010***	-2.09
Total effect	-0.2616**	-2.47
Spatial fixed	YES	
Time fixed	YES	
Number of samples	270	

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

It can be seen from the regression results in Table 9 that the regression coefficient of the digital economy development level (dig) is -0.0664, which passes the test at the 1% significance level. The development of the digital economy has an inhibitory effect on carbon emissions. At the same time, the spatial spillover effect coefficient W*dig of the development of the digital economy is also negative, that is, there is a negative spatial spillover effect, which is consistent with the previous empirical results and confirms the robustness of the conclusions drawn by the model.

5. Conclusions and Recommendations

5.1. Research Conclusion

In the era of digital economy, the realization of carbon peaking, carbon neutrality and dual carbon goals is an important change related to the economy and society. It is urgent to use the digital economy to establish a long-term mechanism for energy conservation and emission reduction. In this context, the internal relationship between the development of the digital economy and carbon emissions is worthy of in-depth exploration. This paper selects 2011-2019 national panel data of 30 provinces and cities except Tibet as research samples, constructs a spatial Durbin model, and studies the impact of digital economy development on carbon emissions from the national and regional levels. The specific research conclusions are as follows:

First, from the perspective of the whole country, there is a positive spatial correlation between China's carbon emissions, and this spatial dependence shows a trend of increasing first and then decreasing. The negative effect of the digital economy on carbon emissions has a greater impact on the region to which it belongs than on adjacent regions.

Second, there are obvious regional differences in the relationship between digital economy development and carbon emission levels in China. Most of the areas with high digital economy development level and high carbon emissions are concentrated in the developed eastern regions. In the eastern region, the development of the digital economy can reduce carbon dioxide emissions and also inhibit carbon emissions in adjacent regions. The reduction effect of the digital economy on carbon emissions in the central region is slightly higher than that in the eastern region, and the spatial spillover effect in the central region shows a positive promoting effect. The development of the digital economy in the western region has no significant effect on carbon emissions.

Third, in the study of control variables, from a national perspective, the level of economic development, industrial structure, and technological innovation ability will all have a negative effect on carbon emissions, while the level of urbanization can promote carbon emissions. With the transformation and upgrading of China's high-quality economic development, the country has increased the investment and use of clean energy and high-tech, which has enabled China to improve the efficiency of energy utilization while economic development, thereby reducing the level of carbon emissions. The adjustment of industrial structure, the talents, and the enhancement of technological innovation capability will reduce carbon dioxide emissions. The improvement of urbanization level has improved the quality of life and energy demand, which in turn has promoted carbon dioxide emissions to a certain extent.

5.2. Policy Recommendations

This paper conducts an in-depth study on the impact of the development of the digital economy from a new perspective of carbon emissions, and can provide corresponding policy suggestions for giving full play to the low-carbon emission reduction effect of the digital economy:

(1) Implement policies according to local conditions and comprehensively consider regional differences to achieve overall emission reduction.

Through empirical research, it is found that there are regional differences in the impact of digital economy on carbon emissions, and the impact of different digital economy scales on carbon emissions is also different. For the western region where the development of digital economy is relatively backward, we should effectively promote the construction of digital economy in combination with the local actual situation. Only when the digital economy develops to a certain scale can we give full play to the environmental dividends brought by the digital economy. For areas with more developed digital economy, we should further consolidate the foundation of digital infrastructure construction, accelerate the integrated development of digital economy and real economy, and provide a feasible path for energy conservation and emission reduction.

(2) Give full play to the role of digital economy in optimizing industrial structure and take the road of modernization and informatization.

The penetration of digital economy in all walks of life is reversing the existing irrational situation of China's industrial structure and realizing industrial upgrading. Therefore, we should develop the interconnection of agriculture, improve farmers' ability to use information technology, introduce information technology talents, and promote rural revitalization with digital economy; We should develop industrial intelligence, improve energy efficiency, and use big data and the Internet to dynamically monitor the pollution discharge of high energy consuming enterprises in real time; We should develop intelligent service industry, use information platform to achieve effective communication and improve service quality.

Author Contributions

Conceptualization, Xinman Lv; methodology, Xinman Lv; software, Xinman Lv; formal analysis, Xinman Lv, Hang Yu and Ying Zhang; writing—original draft preparation, Xinman Lv; writing—review and editing, Xinman Lv; data curation, Hang Yu and Ying Zhang; investigation, Hang Yu and Ying Zhang. All authors have read and agreed to the published version of the manuscript.

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