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The impact of the digital economy on carbon emission intensity: Evidence from China

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Evaluating the impact of the digital economy on carbon emission intensity has great significance in promoting sustainable development. Based on the panel data of 30 provinces in China from 2013 to 2019, the level of the digital economy is estimated by using entropy weight and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) model. The panel vector auto-regressive (PVAR) model is used to analyze the impact of the digital economy on carbon emission intensity. The results show that, first, the comprehensive development level of the digital economy in China is not high, and it tends to rise slowly from 0.208 in 2013 to 0.221 in 2019. Second, the carbon emission intensity of China shows a downward trend from 0.720 in 2013 to 0.607 in 2019. There are significant differences in carbon emission intensity among different regions, and a decreasing trend is seen from the western region to the eastern region. Third, there is a long-term equilibrium relationship between the digital economy and carbon emission intensity. Fourth, the digital economy has a long-term negative effect on carbon emission intensity, but carbon emission intensity has no negative effect on the digital economy. According to the research conclusion, this study puts forward some suggestions.

KEYWORDS

digital economy level, carbon emission intensity, entropy weight method, TOPSIS model, PVAR model

1 Introduction

Since the reform and opening up in 1978, China's economy has developed rapidly. In 2010, China's economy jumped to the second place in the world for the first time (Hou et al., 2021). Although China has made some progress in economic development, the economic development of China mainly relies on fossil fuel consumption. According to the data from the China Energy Statistical Yearbook (2021), the total energy consumption of China was 4.5 billion tons of standard coal in 2020, and the total coal consumption accounted for 62.2%. China's long-term coal-based energy consumption structure has caused serious environmental problems (Zhong et al., 2022). However, with the development of the 5G network, e-commerce, artificial intelligence, and other technologies, the global economy has entered the digital age, and the digital economy has gradually penetrated various fields, such as society and ecology. The digital economy has shown strong carbon emission reduction potential, which has become an important way to alleviate environmental pressure (Yin et al., 2022). In 2021, the scale of the digital economy accounted for 39.8% of China's GDP, ranking second in the world (Yang W et al., 2022). With the huge dividends released by the digital economy, China's economy has gradually changed from extensive development to green and low-carbon development (Zhang et al., 2022). Theoretically, the digital economy is the main

engine of high-quality economic development (Li, 2019; Yin and Yu, 2022). The digital economy has a great impact on people's production and life, but there is little research on the relationship between the digital economy and carbon emission intensity. Can digital economy help to curb carbon emissions? Answering this question has practical significance for promoting economic development and reducing carbon intensity. Therefore, based on the provincial panel data of China, this study uses the panel vector auto-regressive (PVAR) model to analyze the relationship between the digital economy and carbon emission. Compared with the existing literature, the contributions of this study are as follows: First, the determination of evaluation indicators is more scientific, and this paper constructs the index system of the digital economy level based on the input and output dimensions. Second, the research perspective of this paper is more comprehensive, and this paper uses the PVAR model to analyze the relationship between the digital economy and carbon emission intensity.

The arrangement of this paper is as follows: The second part is a literature review, which includes the related literature on the digital economy and carbon emission. The third part is the research design, including introducing the research methods and data sources. The fourth part is the research results, which analyze the level of the digital economy in China, the carbon emission intensity, and the relationship between them. The fifth part is the conclusion, which summarizes this research and puts forward suggestions based on the research findings of this paper.

2 Literature review

Research on the digital economy can be traced back to the late 1990s, when economist Don Tapscott first proposed the concept of "digital economy," pointing out that digital technology can produce new economic forms (Ma and Zhu, 2022). Subsequently, many countries accelerated the formulation of development strategies for the digital economy and actively promoted the development of a digital economy based on information networks and data resources (Sorescu and Schreier, 2021). With the emergence of the new generation of digital technologies, the digital economy not only accelerates the upgrading of the traditional industrial structure but also accelerates the process of digital governance (Sama et al., 2022). Compared with the rapid development of the digital economy, the research on how to measure the development level of the digital economy lags behind. Therefore, academia began to research the index construction and measure the development level of the digital economy (Liu, 2022). Li and Liu (2021), based on the cross-sectional data of eight comprehensive economic zones in China in 2018, evaluated the digital economic level from the aspects of digital infrastructure, digital industry development, and digital application, and found that the development level of the digital economy in China was low. Furthermore, some scholars used the analytic hierarchy process (AHP), an entropy method to calculate the level of the digital economy in China, and found that the digital economy in China was on the rise, and the main influencing factors included the construction of digital infrastructure and the application of digital technology

(Yang and He, 2022). Considering the regional differences in the development of the digital economy, Shi (2022) used the Theil index to analyze the differences in the digital economy in seven regions of China and found the differences in the digital economy among regions were obvious, and the overall trend was on the rise.

In the field of carbon emissions, the academia mainly focuses on how to measure carbon emission measurement, influencing factors of carbon emission, spatial characteristics, and carbon emission reduction paths, and the research objects are provinces, city clusters, and high energy consumption industries. There are many pieces of research measuring carbon emission, carbon emission intensity, and carbon emission efficiency (Cai et al., 2019; Cary, 2020). Through analysis of the influencing factors of carbon emissions, it is found that the factors that promote carbon emissions include the level of industrialization (Wang and Ma, 2018), economic income (Han et al., 2022), energy consumption (Vujović et al., 2018), etc., while the factors that inhibit carbon emissions include activity intensity (Wang et al., 2018), technological input (Wen et al., 2020), environmental regulations (Zhang et al., 2021), etc. Considering the spatial distribution characteristics of carbon emissions, Su et al. (2018) found the regional differences in urban carbon emissions in China showed a downward trend. Yu et al. (2022a) took the Yangtze River Delta region as the research area, used a spatial correlation network model to analyze the spatial correlations of land-use carbon emissions, and found that land-use carbon emissions in the Yangtze River Delta had a spatial correlation and spillover effects. In addition, it is important to reduce the carbon emissions of the construction industry (Dong et al., 2023). Buildings are considered the last mile toward the carbon-neutral century, and studying the decarbonization potential of commercial building operations has become another mainstream topic (Probst et al., 2021; Xiang et al., 2022).

In terms of the relationship between the digital economy and carbon emissions, there are two different opinions about the relationship between the digital economy and carbon emissions. Some scholars believe the digital economy can curb carbon emissions (Yu et al., 2022b). With the development of the digital economy, more and more cities are implementing the concept of low-carbon development because the digital economy encourages the development of digital inclusive finance and green innovative technologies (Ma et al., 2022a; Zheng and Li, 2022). However, the effect of the digital economy on emission reduction is significantly different in different regions. The effect of the digital economy on emission reduction in eastern China is more prominent than in central China and western China (Yi et al., 2022). In addition, the spatial spillover effect of the digital economy on carbon emissions has also become a hot issue in academia. Improving the development level of the digital economy has a significant impact on the reduction of carbon emissions in neighboring areas (Zhou et al., 2022). Other scholars believe the development of the digital economy contributes to the increase in carbon emissions (Avom et al., 2020). The digital economy accelerated China's import trade, resulting in an increase in consumer demand, which amplified consumption-based carbon emissions (Ma et al., 2022b). Liu et al. (2022) found the increase in information and communication technology can increase carbon emissions. In addition, some scholars found the

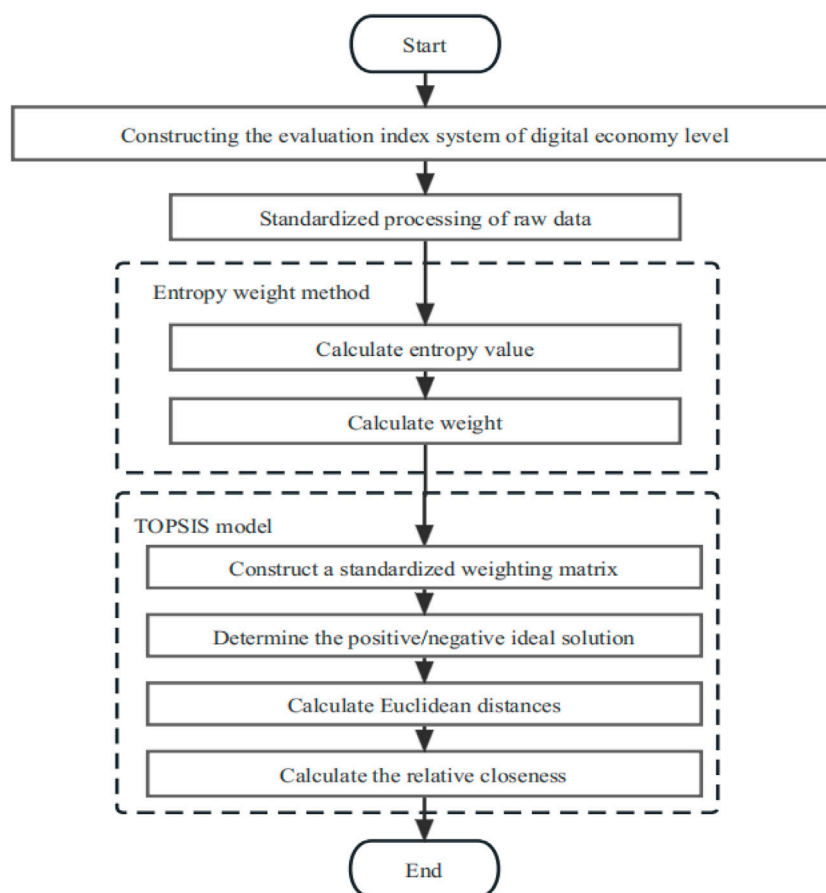


FIGURE 1 Entropy-TOPSIS model.

impact of the digital economy on carbon emissions presents an inverted U-shaped non-linear relationship (Yang Z et al., 2022), which accords with the hypothesis of the environmental Kuznets curve (EKC) (Li et al., 2021).

To sum up, academia has made great achievements in the research of digital economy and carbon emissions, but there are still some research gaps in this field. First, there are many studies on designing digital economic indicators from the perspective of input, but there are few studies on measuring the level of the digital economy from the perspective of input and output. Second, few pieces of literature used the PVAR model to analyze the interactive relationship between the digital economy and carbon emission intensity. The PVAR model not only follows the advantages of the VAR (vector auto-regressive) model but also effectively solves the endogenous and individual heterogeneity problems and accurately reflects the influence of one variable and its lag term on other variables in the model (Dai et al., 2022). Therefore, based on the panel data of 30 provinces in China from 2013 to 2019, this paper first uses the entropy weight-TOPSIS method to evaluate the level of the digital economy in China, then calculates the carbon emission intensity based on the carbon emission coefficient method, and finally, uses the PVAR model to explore the relationship between the digital economy and carbon emission intensity.

3 Research methods and variable description

3.1 Research methods

3.1.1 Entropy-TOPSIS model

In this paper, the entropy weight method and TOPSIS model are combined to evaluate the level of the digital economy in China. The main idea is to standardize the processing of index data, then use the entropy weight method to determine the index weight, and finally use the TOPSIS model to determine the ranking of the digital economy level (Deng et al., 2020; Li S et al., 2022). The process of the entropy-TOPSIS method is as follows (see Figure 1).

Step 1: Standardization of raw data.

$$\text{Positive indicators: } y_{jn} = \frac{x_{jn} - m(x_{jn})}{M(x_{jn}) - m(x_{jn})} \quad (1 < j < i, 1 < n < m) \tag{1}$$

$$\text{Negative indicators: } y_{jn} = \frac{m(x_{jn}) - x_{jn}}{M(x_{jn}) - m(x_{jn})} \quad (1 < j < i, 1 < n < m) \tag{2}$$

TABLE 1 Digital economic index system.

Target layer	Criteria layer	Primary index	Secondary indicators (units)
Digital economy	Invest	Digital infrastructure	Telephone penetration rate (mobile/hundred people), number of internet broadband access ports (10,000), Number of IPV4 addresses (10,000), number of domain names (10,000)
		Digital innovation elements	Proportion of scientific expenditure to fiscal expenditure (%), number of R&D personnel (person), proportion of R&D funds to GDP (%), number of patent applications (pieces), average number of students in higher education per 100,000 population (person)
	Output	Digital industry	Software business income (10,000 Yuan), telecom business income (100 million Yuan), income from express delivery business (10,000 Yuan)
		Industrial digitalization	Number of websites owned by each hundred enterprises (pieces), E-commerce sales (100 million Yuan), the proportion of enterprises with e-commerce activities (%)

In Formulas 1 and 2, x_{jn} represents the sample value of the n -th index in the j -th object, $M(x_{jn})$ is the maximum value of the sample values, and $m(x_{jn})$ is the minimum value of the sample values.

Step 2: Calculating the index weight.

$$H_n = \left[-\frac{1}{\ln(j)} \right] \sum_{j=1}^i \left[\frac{y_{jn}}{\sum_{j=1}^i y_{jn}} \times \ln \left(\frac{y_{jn}}{\sum_{j=1}^i y_{jn}} \right) \right] \tag{3}$$

$$w_n = \frac{1 - H_n}{\sum_{n=1}^m (1 - H_n)} \tag{4}$$

In Formulas 3 and 4, H_n represents the entropy value of each index, and w_n represents the weight of each index.

Step 3: Calculating the Euclidean distance and relative closeness.

First, we construct a standardized weighting matrix Q .

$$Q = q_{jn} = w_n \times \frac{y_{jn}}{\sum_{j=1}^i y_{jn}} \tag{5}$$

Second, we determine the positive ideal solution Q^+ and negative ideal solution Q^- .

$$Q^+ = [q_1^+, q_2^+, \dots, q_m^+] \tag{6}$$

$$Q^- = [q_1^-, q_2^-, \dots, q_m^-] \tag{7}$$

Third, we calculate the Euclidean distances D^+ and D^- .

$$D^+ = \sqrt{\sum_{n=1}^m (Q - Q^+)^2} \tag{8}$$

$$D^- = \sqrt{\sum_{n=1}^m (Q - Q^-)^2} \tag{9}$$

Fourth, we calculate the relative closeness P .

$$P = \frac{D^-}{D^+ + D^-} \quad (0 < P < 1) \tag{10}$$

3.1.2 Panel vector auto-regressive model

This study chose the PVAR and Gaussian mixture model (GMM) methods to analyze the relationship between the digital economy level and carbon emission intensity. The PVAR

model not only follows the advantages of the vector auto-regressive (VAR) model but also effectively solves the endogenous and individual heterogeneity problems and accurately reflects the influence of one variable and its lag term on other variables in the model (Dai et al., 2022). The formula is as follows:

$$Z_{it} = \beta_0 + \sum_{j=1}^n \beta_j Z_{i,t-j} + f_i + g_t + h_{it} \quad (i = 1, 2, \dots, 30; t = 1, 2, \dots, 7) \tag{11}$$

In Formula (11), Z_{it} is an endogenous variable, including digital economy level (CE) and carbon emission intensity (CO_2). β_0 represents the intercept term, j represents the lag order, f_i represents the individual effect, g_t represents the time effect, and h_{it} represents the random error term.

3.2 Variable description and data sources

3.2.1 Digital economy level

Ding et al. (2021) pointed out that the digital economy is the economic output brought by the digital input. Combined with China's digital economy development report, this study designs two criteria layers of input and output. Furthermore, it is subdivided into four first-level indicators, the digital input is represented by digital infrastructure and digital innovation elements, and the digital output is represented by digital industry and industrial digitalization (see Table 1). Referring to the research of Li and Wang (2022), digital infrastructure includes telephone penetration rate, the number of internet broadband access ports, and the number of domain names. Referring to the research of Zhao et al. (2022a), innovative elements include the number of scientific research and experimental development (R&D) personnel, the proportion of R&D funds to gross domestic product (GDP), etc. Referring to the research of Wang and Shi (2021), the digital industry refers to software business income and telecom industry income, and industrial digitalization refers to the number of websites owned by every hundred enterprises and e-commerce sales. The data of this paper comes from China Statistical Yearbook (2014–2020), and some missing data are filled in by interpolation.

TABLE 2 Development level of the digital economy in China from 2013 to 2019.

Region	Province	2013	2014	2015	2016	2017	2018	2019
Eastern China	Guangdong	0.869	0.789	0.879	0.879	0.881	0.890	0.896
	Jiangsu	0.580	0.516	0.624	0.619	0.609	0.643	0.660
	Zhejiang	0.480	0.615	0.523	0.513	0.511	0.539	0.552
	Beijing	0.478	0.695	0.474	0.477	0.464	0.452	0.450
	Shanghai	0.454	0.622	0.481	0.470	0.460	0.459	0.468
	Shandong	0.501	0.337	0.441	0.450	0.451	0.428	0.401
	Fujian	0.242	0.435	0.280	0.269	0.281	0.292	0.294
	Liaoning	0.248	0.388	0.275	0.265	0.262	0.269	0.270
	Tianjin	0.205	0.281	0.221	0.206	0.199	0.207	0.198
	Hebei	0.137	0.183	0.159	0.150	0.158	0.165	0.166
	Hainan	0.101	0.256	0.099	0.094	0.092	0.099	0.106
	Average		0.390	0.465	0.405	0.399	0.397	0.404
Central China	Anhui	0.184	0.136	0.197	0.192	0.192	0.203	0.203
	Hubei	0.166	0.169	0.179	0.171	0.173	0.182	0.181
	Henan	0.157	0.144	0.164	0.159	0.159	0.168	0.169
	Hunan	0.140	0.115	0.156	0.149	0.155	0.165	0.165
	Jiangxi	0.110	0.099	0.139	0.134	0.149	0.153	0.156
	Shanxi	0.096	0.188	0.113	0.106	0.106	0.109	0.106
	Heilongjiang	0.112	0.169	0.105	0.103	0.106	0.101	0.093
	Jilin	0.075	0.213	0.088	0.083	0.082	0.086	0.086
	Average		0.130	0.154	0.143	0.137	0.140	0.146
Western China	Sichuan	0.184	0.180	0.201	0.195	0.198	0.205	0.206
	Shaanxi	0.118	0.257	0.128	0.119	0.118	0.126	0.126
	Chongqing	0.117	0.183	0.129	0.120	0.121	0.130	0.127
	Inner Mongolia	0.069	0.292	0.086	0.076	0.072	0.082	0.083
	Xinjiang	0.059	0.262	0.076	0.069	0.065	0.071	0.072
	Ningxia	0.072	0.234	0.077	0.070	0.066	0.074	0.076
	Guangxi	0.079	0.053	0.086	0.083	0.084	0.084	0.084
	Qinghai	0.049	0.228	0.059	0.053	0.048	0.056	0.059
	Yunnan	0.067	0.077	0.069	0.068	0.070	0.072	0.073
	Gansu	0.053	0.115	0.055	0.049	0.049	0.054	0.053
	Guizhou	0.049	0.090	0.051	0.049	0.049	0.051	0.051
	Average		0.083	0.179	0.093	0.087	0.086	0.091
National average		0.208	0.277	0.221	0.215	0.214	0.220	0.221

3.2.2 Carbon emission intensity

Carbon emission intensity is measured by the proportion of carbon emissions to GDP (gross domestic product). The specific formula is as follows:

$$CO_2 = \frac{C_i}{GDP} \tag{12}$$

In Formula(12), referring to the research of Zhao et al. (2022b), this paper selects the eight kinds of carbon sources,

TABLE 3 Carbon emission intensity in China from 2013 to 2019.

Region	Province	2013	2014	2015	2016	2017	2018	2019
Eastern China	Guangdong	0.298	0.276	0.258	0.240	0.227	0.217	0.194
	Jiangsu	0.401	0.367	0.354	0.334	0.299	0.276	0.263
	Zhejiang	0.352	0.328	0.311	0.280	0.270	0.244	0.228
	Beijing	0.188	0.183	0.167	0.142	0.129	0.123	0.105
	Shanghai	0.403	0.338	0.330	0.294	0.276	0.247	0.220
	Shandong	0.630	0.628	0.631	0.629	0.592	0.587	0.649
	Fujian	0.338	0.359	0.322	0.273	0.258	0.254	0.230
	Liaoning	0.801	0.762	0.741	0.964	0.943	0.933	1.043
	Tianjin	0.444	0.393	0.369	0.324	0.313	0.322	0.434
	Hebei	0.948	0.872	0.856	0.797	0.735	0.765	0.793
	Hainan	0.621	0.627	0.655	0.582	0.513	0.495	0.466
	Average	0.493	0.467	0.454	0.442	0.414	0.406	0.420
Central China	Anhui	0.571	0.546	0.517	0.465	0.436	0.408	0.332
	Hubei	0.418	0.384	0.353	0.320	0.303	0.269	0.245
	Henan	0.556	0.517	0.489	0.444	0.383	0.345	0.282
	Hunan	0.369	0.325	0.321	0.296	0.287	0.254	0.232
	Jiangxi	0.415	0.386	0.380	0.350	0.330	0.313	0.284
	Shanxi	1.783	1.813	1.798	1.709	1.684	1.765	1.835
	Heilongjiang	0.745	0.726	0.720	0.722	0.698	0.625	0.788
	Jilin	0.613	0.574	0.527	0.493	0.487	0.457	0.607
	Average	0.684	0.659	0.638	0.600	0.576	0.554	0.576
Western China	Sichuan	0.412	0.399	0.358	0.316	0.273	0.230	0.216
	Shaanxi	0.847	0.817	0.794	0.756	0.683	0.599	0.615
	Chongqing	0.349	0.336	0.308	0.270	0.249	0.222	0.193
	Inner Mongolia	1.298	1.266	1.258	1.251	1.482	1.574	1.754
	Xinjiang	1.543	1.564	1.567	1.598	1.508	1.395	1.328
	Ningxia	2.237	2.129	2.087	1.912	2.160	2.210	2.368
	Guangxi	0.472	0.435	0.387	0.373	0.390	0.367	0.372
	Qinghai	0.904	0.779	0.692	0.751	0.709	0.636	0.609
	Yunnan	0.609	0.505	0.425	0.388	0.372	0.395	0.317
	Gansu	1.011	0.939	0.920	0.836	0.817	0.766	0.733
	Guizhou	1.027	0.865	0.758	0.718	0.615	0.527	0.477
	Average	0.974	0.912	0.868	0.833	0.842	0.811	0.817
National average		0.720	0.681	0.655	0.627	0.614	0.594	0.607

such as coal and natural gas, to calculate the carbon emission (C_i) in combination with the carbon emission coefficient. The formula is as follows:

$$C_i = \sum_{i=1}^8 E_i \times \alpha_i \times \mu_i \tag{13}$$

In **Formula (13)**, E_i represents the energy consumption, α_i represents the carbon emission coefficient, and μ_i represents the standard coal conversion coefficient. The data comes from China Energy Statistics Yearbook (2014–2020), and some missing data are filled in by interpolation.

4 Results and discussion

4.1 Comprehensive evaluation of the development level of digital economy

The entropy weight–TOPSIS method is used to evaluate the level of the digital economy. The specific results are shown in Table 2.

As can be seen from Table 2, the level of the digital economy in China increased from 0.208 in 2013 to 0.221 in 2019, with an increase of 6.25%, indicating the level of the digital economy is slowly rising. Specifically, the level of the digital economy rose sharply from 2013 to 2014, reached 0.277 in 2014, then showed a downward trend from 2014 to 2017, and slowly rose from 2017 to 2019. In addition, there are significant differences in the level of the digital economy in China, which is consistent with the research of Xu et al. (2021). In 2019, the average value of the digital economy was 0.221 in China, 0.406 in eastern China, 0.145 in central China, and 0.092 in western China. The level of the digital economy in eastern China is higher than the national average, while that in central China and western China is significantly lower than the national average, which shows the development among regions is unbalanced, and the level of the digital economy decreases from the eastern region to western region. It is because the eastern region has a superior geographical location and a good economic and talent base, which creates conditions for technological innovation. However, the economic development level in central China and western China is low, which leads to a weak foundation of digital economy development and a slow growth rate. Second, Guangdong Province in eastern China ranked first in digital economy level, and Hainan Province ranked 19th, which is far behind other provinces in eastern China. The average values of the digital economy in Xinjiang, Ningxia, Guangxi, Qinghai, Yunnan, Gansu, and Guizhou in the western region are below 0.1, and while Sichuan ranks 10th, Sichuan's digital economy is growing faster than other provinces in the western region. As can be seen from Table 2, there are great differences in the development of digital economy in different provinces.

4.2 Measurement of carbon emission intensity

Based on the carbon emission coefficient method, this study evaluates the carbon emission intensity of different provinces in China from 2013 to 2019, and the results are shown in Table 3.

As can be seen from Table 3, China's carbon emission intensity shows a downward trend, with the carbon emission intensity decreasing from 0.720 in 2013 to 0.607 in 2019. This is consistent with the research conclusion by Wang and Zheng (2021). It is worth noting that the carbon intensity levels of Shanxi and Ningxia in 2013 and 2019 were at high levels. The reasons are as follows: First, Shanxi and Ningxia have great responsibilities in safeguarding national energy, so the coal development intensity is high, but the economic level is low, and the growth rate is slow, resulting in the high carbon intensity. Second, it is difficult to transform the energy consumption structure and the industrial structure. The carbon emission intensity of Inner Mongolia increased from 1.298 in 2013 to

1.754 in 2019, an increase of 35.13%. According to the resource curse theory (Wu et al., 2021), Inner Mongolia is constrained by a heavy industrial structure, which has the development dilemma of high energy consumption and low output value. In addition, the preferential electricity price policy in Inner Mongolia has also promoted the transfer of high energy-consuming industries, resulting in the carbon intensity of Inner Mongolia rising instead of falling. In addition, the carbon emission intensity of China has a discrepancy, showing a decreasing trend from western China to eastern China. This is because a series of projects, such as power transmission from western China to eastern China and gas transmission from western China to eastern China, have been started after the western development, and the rapid economic development in western China has caused air pollution. Because the projects have the characteristics of a long cycle and large scale, it is difficult to reduce the carbon emission intensity in western China.

4.3 The relationship between digital economy and carbon emission intensity

4.3.1 Unit root test

To ensure the accuracy of this paper and avoid false regression caused by unstable variables (Duan et al., 2022), this paper uses the unit root test, including the Levin–Lin–Chu test (LLC), different root Im–Pesaran–Shin test (IPS), and short panel Harris–Tzavalis test (HT). The results show that the LLC, IPS, and HT tests of the digital economy level ($\ln CE$) all reject the original hypothesis at a 1% significance level. In other words, the original sequence is stable, and the unit root test is passed. The original sequence of carbon emission intensity ($\ln CO_2$) failed the IPS and HT tests. This means the original sequence has a unit root. The results in Table 4 show that the digital economy and the carbon emission intensity that the first-order difference data have passed LLC, IPS, and HT tests. It indicates that the two variables are first-order single integration, which can be used for the co-integration test.

4.3.2 Co-integration test

Based on the single integration of the same order, the co-integration test is used to further analyze whether there is a long-term co-integration relationship between variables (Li Z et al., 2022). This paper used the Pedroni and Kao tests to test the co-integration relationship between the digital economy and carbon emission intensity. The original assumption is that there is no co-integration relationship between variables. The results in Table 5 show that the Pedroni and Kao tests reject the original hypothesis at 1% significance level. In other words, there is a long-term equilibrium relationship between digital

TABLE 4 Unit root test.

Variable	LLC	IPS	HT
$\ln CE$	-26.206 (0.000)	-9.589 (0.000)	-0.501 (0.000)
$\ln CO_2$	-6.108 (0.000)	2.919 (0.998)	0.176 (0.500)
$\Delta \ln CE$	-42.311 (0.000)	-24.029 (0.000)	-0.466 (0.000)
$\Delta \ln CO_2$	-8.428 (0.000)	-2.183 (0.015)	-0.077 (0.000)

TABLE 5 Co-integration test.

Test	Statistical indicators	Statistics	p value
Pedroni	Modified Phillips–Perron t	4.502	0.000***
	Phillips–Perron t	−29.770	0.000***
	Augmented Dickey–Fuller t	−135.919	0.000***
Kao	Modified Dickey–Fuller t	4.500	0.000***
	Dickey–Fuller t	−6.901	0.000***
	Augmented Dickey–Fuller t	6.624	0.000***
	Unadjusted modified Dickey	−3.341	0.004***
	Unadjusted Dickey–Fuller t	−22.182	0.000***

***, **, and * represent significance levels of 1%, 5%, and 10%, respectively; the robust standard error is in brackets.

economy level and carbon emission intensity, and the PVAR model can be used.

4.3.3 Optimal lag order test

Before using the PVAR model, it is necessary to discriminate the optimal lag order of variables. Among them, the optimal lag order is determined according to the minimum value of AIC (Akaike information criterion), BIC (Bayesian information criterion), and HQIC (Hannan–Quinn information criterion) (Yuan et al., 2022). The results in Table 6 show that the optimal lag order selected by BIC is first order and the optimal lag order selected by AIC and HQIC is second order. According to the majority vote principle, the optimal lag period of the model is determined to be second order.

4.3.4 GMM estimation based on the PVAR model

GMM is used to estimate the parameters of digital economy level (*lnCE*) and carbon emission intensity (*lnCO₂*), and the estimated results are shown in Table 7. Column (1) is the regression result which takes the digital economy level as the explained variable. The result shows that the coefficient between carbon emission intensity lagging by two periods and the digital economy level is negative, but it fails to pass the significance level test, which indicates that the effect of carbon emission intensity on the digital economy level is not strong in the short term. Column (2) is the regression result which takes carbon emission intensity as the explained variable. The result shows that the digital economy level lagging by two periods has a significant inhibitory effect on carbon emission intensity, indicating that the higher the digital economy level the lower the carbon emission intensity. This is because the digital economy is driving the economy from factor-driven to innovation-driven, which not only helps to optimize the industrial structure, but also helps to improve energy efficiency. This transformation stimulates the high-quality development of the economy and reduces carbon emission intensity. It is consistent with the research of Wang et al. (2022a). In other words, the digital economy has a significant negative effect on carbon emissions. The difference between the research of Wang et al. (2022b) and this study is that this paper considers endogenous variables and uses the PVAR model to analyze the two-way interactive relationship between the digital

TABLE 6 Test results of optimal lag order.

Lag	AIC	BIC	HQIC
1	−0.539	−25.671*	−10.369
2	−7.925*	−24.679	−14.479*
3	−6.381	−14.759	−9.658

*The optimal lag order selected by the corresponding criteria.

economy and carbon emissions, deepening the relevant research results.

4.3.5 Impulse response analysis

To analyze the impact changes between digital economy level and carbon emission intensity, the impulse response function is used for dynamic analysis. Referring to Wang et al. (2022a), the number of sample periods set by the model is 10. Combined with the Monte Carlo method, the number of repetitions of data simulation is 500, and the impulse response function results are shown in Figure 2. In Figure 2, the horizontal axis indicates the number of lag periods, the vertical axis indicates the degree of the impulse response, the upper and lower dashed lines indicate the upper and lower bounds of the 95% confidence interval, and the solid line in the middle indicates the impulse response value of the response variable after being impacted by a standard deviation unit.

As can be seen from Figure 2A, the level of the digital economy has a positive response to itself, reaching the maximum value in the current period and showing a downward trend as a whole. In the second period, the maximum negative response is reached, and it begins to show an upward trend. In the third period, it rises to zero. It shows that the level of the digital economy is strengthened by itself and has a long-term promoting effect. As can be seen from Figure 2B, the impact of the digital economy on carbon emission intensity is negative and gradually becomes stable. Specifically, the level of the digital economy has a negative impact on carbon emission intensity from the current period, reaching the maximum negative impact in the second period. However, the overall trend rises and is kept stable below zero level. It shows that the improvement of the digital economy can inhibit carbon

TABLE 7 GMM parameter estimation results.

Variable	(1)lnCE	(2)lnCO ₂
L2.lnCE	-0.038** [0.019]	-0.699* [0.041]
L2.lnCO ₂	-0.022 [0.085]	0.098 [0.124]

***, **, and * represent significance levels of 1%, 5%, and 10%, respectively; the robust standard error is in brackets.

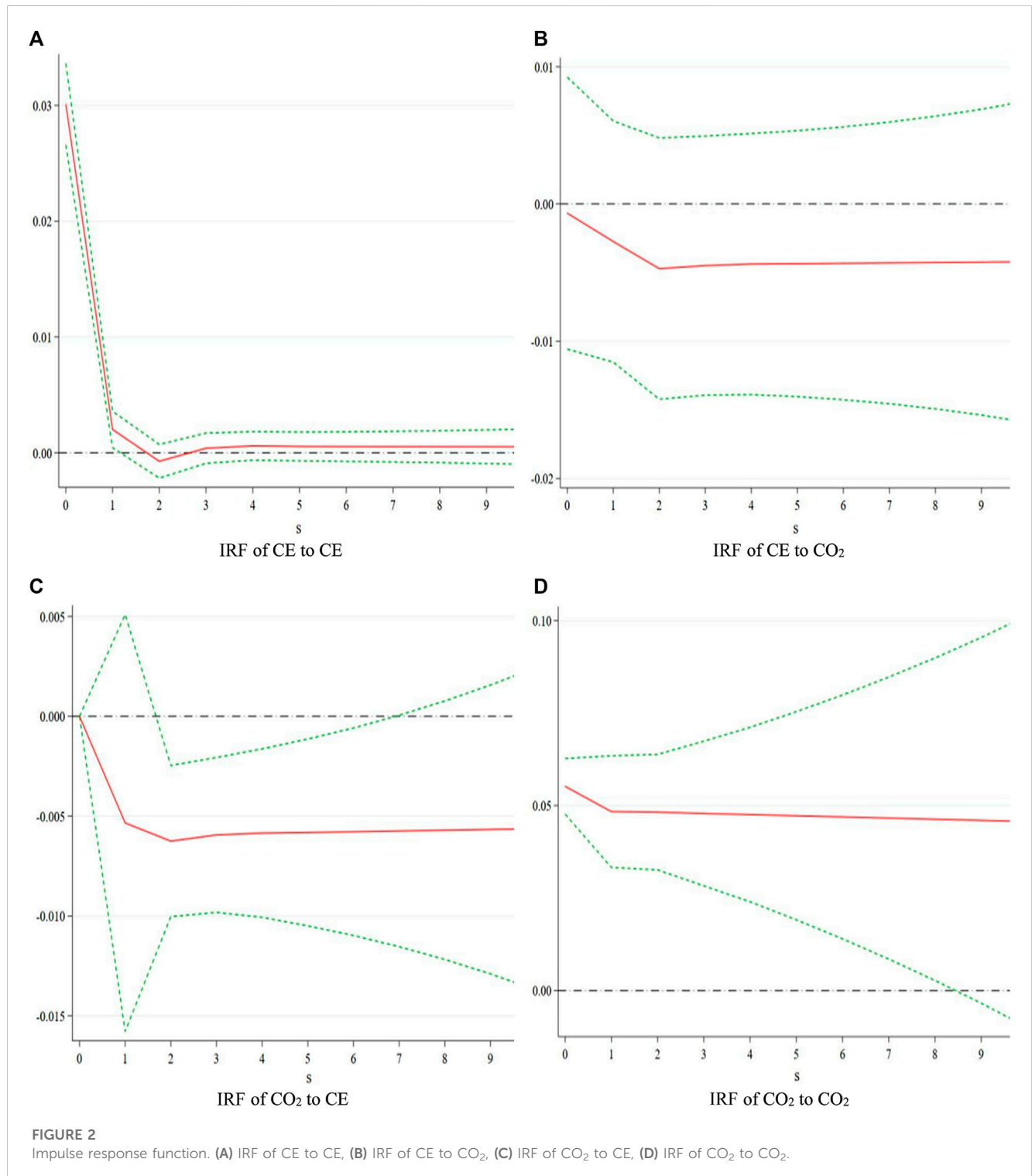


TABLE 8 Variance decomposition.

Variable	Variable contribution rate			Variable	Variable contribution rate		
	Stage	lnCE	lnCO ₂		Stage	lnCE	lnCO ₂
lnCE	1	1.000	0.000	lnCO ₂	1	0.000	1.000
	2	0.970	0.030		2	0.001	0.999
	3	0.931	0.069		3	0.004	0.996
	4	0.899	0.101		4	0.005	0.995
	5	0.869	0.131		5	0.006	0.994
	6	0.842	0.158		6	0.006	0.994
	7	0.817	0.183		7	0.006	0.994
	8	0.794	0.206		8	0.007	0.993
	9	0.772	0.228		9	0.007	0.993
	10	0.751	0.249		10	0.007	0.993

emission intensity. On the whole, in the short term, the digital economy plays a prominent role in restraining carbon emission intensity, while in the long term, the impact of the digital economy on carbon emission intensity has a certain time lag, which indicates the impact of the digital economy on carbon emission intensity is more lasting and far-reaching. Existing studies have shown that the digital economy promotes green economic development. For example, Song et al. (2022) found that the development of the digital economy can improve urban air quality. Kong and Li (2022) found that the development of the digital economy is helpful in improving the efficiency of a green economy. This study discusses the relationship between the digital economy and carbon intensity and finds digital economy contributes to the reduction of carbon intensity, expanding related research. Figure 2C shows a downward trend after the impact of carbon emission intensity on the digital economy level and tends to be stable after the third period, indicating carbon emission intensity has a long-term inhibitory effect on the digital economy level. Figure 2D shows that after the impact of one standard deviation of carbon emission intensity, its effect begins to decline and gradually becomes stable after reaching the maximum value in the current period, which indicates carbon emission intensity has a significant promoting effect on itself.

4.3.6 Variance decomposition

In this paper, variance decomposition is utilized to analyze the contribution of various structural impulses to the fluctuation of the digital economy level and carbon emission intensity. The results are shown in Table 8.

As can be seen from Table 8, in terms of lnCE (digital economy level), the contribution of lnCE to itself reaches 75.1% in period 10, while the variance contribution of lnCO₂(carbon emission intensity) is 24.9%. It can be seen that the contribution rate of lnCE mainly comes from itself and lnCO₂. In terms of lnCO₂, the variance contribution of lnCO₂ to itself is higher in period 10, which is more than 99% stable, while the contribution rate of lnCE to lnCO₂ is lower in period 10, which is less than 1% stable. It indicates that the

self-strengthening ability of lnCO₂ is stronger. From the results of variance decomposition, we can see that the variance contribution rate of the digital economy and carbon emission intensity mainly comes from its own strengthening. In the long run, the impact of carbon emission intensity on the level of the digital economy has been strengthened over time.

5 Conclusion

Based on the data from 30 provinces in China from 2013 to 2019, this study analyzes the impact of digital economy development on carbon emission intensity. The research findings are as follows: 1) The development level of digital economy development in China is not high but has a slow upward trend. The development level of the digital economy in China has significant differences in different provinces. Specifically, the development level of the digital economy is decreasing from eastern China to western China. This indicates that while accelerating the development of the digital economy, China needs to pay attention to the regional differences in the digital economy. 2) China’s carbon emission intensity has declined, and the regional differences are significant. Specifically, the carbon emission intensity in eastern China is the lowest, followed by central China, and highest in western China. 3) Through the co-integration test, there is a long-term equilibrium relationship between the digital economy and carbon emission intensity. In addition, the optimal lag period of the model is 2. The GMM estimation results based on the PVAR model show the digital economy lagging behind two periods and significantly inhibiting carbon emission intensity. 4) From impulse response analysis, the digital economy has a long-term inhibitory effect on carbon emission intensity. This shows the digital economy has a certain climate improvement effect, and promoting the development of the digital economy can reduce the carbon emission intensity.

Based on the research findings, the following suggestions are put forward:

1) We should strengthen the construction of digital infrastructure such as internet broadband, 5G base stations, and artificial intelligence and, at the same time, actively apply digital technology to change resource waste. 2) China should strengthen the input of digital innovation elements. On the one hand, the government should rationally arrange financial expenditure and improve the coverage and innovation of information technology to empower the rapid development of the digital economy. On the other hand, high-quality digital talents should be cultivated to enhance the application ability of information technology and to provide a talent guarantee for the improvement of the digital economy. 3) We should steadily promote the development of industrial digitalization and intensify the development of the digital industry. In terms of industrial digitalization, enterprises need to penetrate internet technology into every link of production and operation to create a new format of enterprise development. In terms of the digital industry, the current development level is low, and the speed is slow. Therefore, the government needs to increase the support of innovation policies to create a good business environment for the development of the digital industry. 4) Cooperation should be strengthened and digital economy policies should be issued in line with regional characteristics. The eastern region should increase investment in information technology innovation capability, and the central and western regions should increase investment in digital infrastructure and digital innovation elements, thus helping the high-quality development of the digital economy.

This study analyzes the relationship between the digital economy and carbon emissions of 30 provinces in China, but there are still some shortcomings. First, there are significant differences in the digital economy level and carbon emission intensity in different regions of China, so it is a future research direction to study the relationship between the digital economy level and carbon emission intensity in different regions. Second, the factors related to the two variables of the digital economy level and carbon emission intensity are diverse and complex. In the future, other influencing factors should also be considered to further improve the research conclusions. Third, the study period of this paper is only 7 years, which can be appropriately increased in the future.

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Data availability statement

The raw data supporting the conclusion of this article will be made available by the authors, without undue reservation.

Author contributions

XZ and MJ drafted the manuscript. YZ conceptualized and designed the study. XZ contributed to materials and analysis. YZ contributed to the theories and revised the manuscript. All authors read and agreed to the published version of the manuscript.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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