



# The Impact of the Digital Economy on Provincial Carbon Emissions in China

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## Abstract

With the arrival of the Fourth Industrial Revolution, digital changes have occurred in various areas, such as production, circulation, and exchange, triggering efficiency and quality changes in the entire economic system and bringing new opportunities for China's energy conservation and carbon reduction policies. Based on the panel data of 30 provinces in China from 2006 to 2020, this paper uses ArcGIS software and the Moran index method to analyze the spatial distribution characteristics and agglomeration effects of the digital economy and carbon emissions and uses the spatial Durbin model to analyze the impact mechanism of the digital economy on carbon emissions. The results show that the development of the digital economy can significantly suppress provincial carbon emissions, and the carbon reduction effect of the digital economy has a significant positive spatial spillover effect. The digital economy can reduce carbon emissions by promoting technological innovation and optimizing the industrial structure. However, the carbon emission reduction effect of energy structure optimization is uncertain due to energy rebound effects. The digital economy has a suppressive effect on carbon emissions in both the eastern and western regions, while the development of the digital economy in the central region increases carbon emissions due to factors such as the "resource curse", income effects and energy rebound effects. Digital economy development plays an inhibitory role in the carbon emissions of regions, with the greater the digital economy level, the more significant the inhibitory effect. Based on the above results, corresponding suggestions are proposed to strengthen the development of the digital economy and promote carbon reduction.

**Keywords** Digital economy · Carbon emissions · Impact mechanism · Spatial durbin model

## Introduction

As China's economy enters a stage of high-quality development, it is urgent to overcome resource and environmental constraints. The need for quality change, efficiency change and power change in economic development is increasingly urgent. At the same time, in the context of the fourth Industrial Revolution, with the rapid development and widespread application of advanced technologies such as big data, blockchain, and artificial intelligence, the production, circulation, and trading of society have undergone systematic and disruptive changes, moving towards digitization, intelligence, and low-carbon green development. According to the White Paper on China's Digital Economy Development (2022) issued by the China Academy of Information and Communications Technology, the scale of China's digital economy reached 45.5 trillion yuan in 2021, an increase of 16.2% compared to that of the previous year, and the average annual growth rate of China's digital economy reached 15.9% since 2012, which is significantly greater than the average GDP growth during the same period. The role of the digital economy as a "stabilizer" and "accelerator" of the national economy has become more prominent. As a new economic form, the digital economy is promoting structural and breakthrough changes in production, circulation, exchange and other aspects, making intelligent production, intelligent logistics, and digital trade possible and providing new impetus to promote energy conservation, emission reduction and high-quality development of economic and social systems (Miao, 2021; Xie & Guo, 2022; Lafuente et al., 2019).

However, in research on the digital economy and environmental pollution, scholars studying the micromechanisms, mechanisms, and empirical testing of the relationship between the digital economy and environmental pollution have reached different conclusions based on the different perspectives and methodologies adopted.

First, some scholars contend that developing the digital economy improves environmental quality and reduces carbon emissions. This belief is grounded in the idea that the digital economy can mitigate carbon emissions through digital finance, governance effects, and corporate impacts (Zhao et al., 2023). The supporting literature demonstrates that diverse forms of the digital economy play a role in curbing carbon emissions, such as leveraging ICT development for clean technology enhancement (Haini et al., 2021), the widespread use of internet technology (Awan et al., 2022; Hal-dar et al., 2022), enhancements in digital infrastructure, the growth of digital industries, and the increased adoption of digital applications (Luo et al., 2022; Wang et al., 2022). At the micro level, from the perspective of digital finance, its development significantly reduces carbon emissions and enhances carbon emission efficiency by fostering economic growth, influencing industrial structure, and driving technological innovation (Deng et al., 2021). From the standpoint of government governance, the digital economy improves the government's ability to manage carbon emissions (Chen et al., 2021). The establishment of a digital technology platform enhances the efficiency of the government's daily affairs, including carbon emissions, contributing to the carbon peak and promoting low-carbon practices. Regarding the enterprise effect, the digital economy can stimulate the low-carbon transformation of industrial enterprises (Lyu et al., 2021; Dong et al., 2022) by upgrading their industrial informatization, automation, and intelligence, thus improving energy allocation efficiency

and reducing energy waste (Thompson et al., 2013). While research results regarding the factors affecting carbon emissions in the digital economy are promising, practical implementation is essential. Existing studies highlight that the development of e-finance and the deployment of ICT in China have proven effective in reducing carbon dioxide emissions (Elheddad et al., 2021; Zhang et al., 2015).

Second, many scholars argue that developing the digital economy will contribute to an increase in carbon dioxide emissions. This perspective arises from the potential environmental consequences of growth in digital economy subsectors, such as the internet and ICT products, which can lead to substantial ambient air pollution (Sinha, 2018; Avom et al., 2020). The literature supporting this view maintains a negative stance towards ICT, its upstream and downstream industries, and ICT carriers, asserting that they will contribute to heightened carbon dioxide emissions (Zhou et al., 2019; Usman et al., 2021). The digital economy has permeated every aspect of the economy, society, and daily life (Li et al., 2022), enhancing human convenience. However, within the temporal-output relationship, increased convenience often leads to heightened human activities, subsequently resulting in increased carbon emissions (Mohammad et al., 2020). Examples include the shift from horses, airplanes, and paper letters to e-mail (Blake, 2005). Moreover, optimizing industrial production through the digital economy has improved industrial efficiency and spurred demand. For instance, more fuel-efficient cars may increase the frequency of driving (Daniel, 1980). Scholars are now concentrating on quantifying carbon emissions from the ICT sector, asserting that 50% of the carbon footprint is associated with PC equipment (Honee et al., 2012), and the ICT sector contributes 3.6% of total emissions (Asongu et al., 2018). Technological advancements, particularly the increased penetration of tablets and smartphones, have resulted in 1.3% of carbon emissions from the entertainment and media sector (Malmodin et al., 2016). Beyond the digital economy's impact on carbon emissions, researchers have shown that industrial structure positively influences economic growth (Gan et al., 2011a, b). The cumulative effect of economic level stands out as the most substantial among the various drivers of carbon emissions (Liu et al., 2024), indicating that industrial structure significantly affects carbon emissions. Additionally, energy consumption (Obindah et al., 2024) and technological innovation (Zhao et al., 2023) can influence carbon emissions by propelling economic development, fostering social progress, and accelerating human activities (Song et al., 2023).

Additionally, from a theoretical perspective, some studies suggest a nonlinear relationship between the digital economy and emissions. For instance, spatial econometric models reveal an inverted U-shaped impact of the digital economy on carbon emissions and spatial spillover effects, along with spatial heterogeneity (Li et al., 2022). It is observed that cities with higher levels of economic development may exhibit poorer environmental quality but with a threshold effect. After reaching a certain threshold, the linear trend decreases (Wang et al., 2021; Yu et al., 2023).

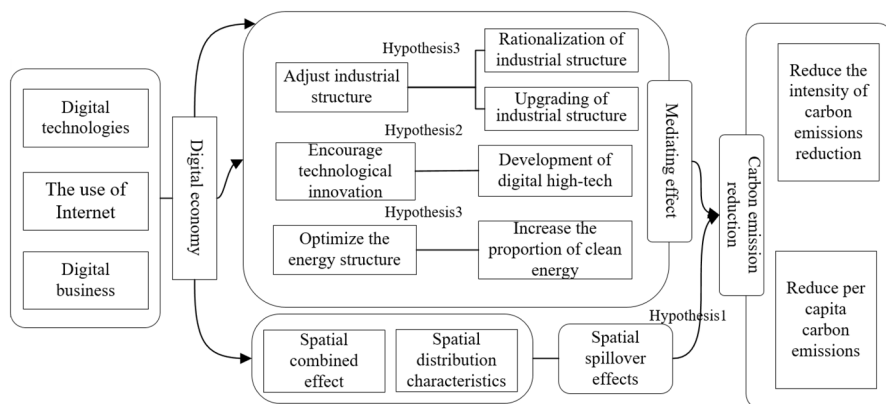
A literature review shows that scholars have made significant achievements in the research on the relationship between the digital economy and carbon emissions, but there are still three deficiencies to be addressed. First, most studies have examined the impact of the digital economy on carbon emissions from one or several perspectives, such as ICT, digital technology and the use of the internet, but few studies have

analyzed the digital economy as a comprehensive index or a new economic format. Second, regarding the mechanism of the impact of the digital economy on carbon emissions, scholars lack comprehensive studies on the mediating role of technological innovation or the optimization of the industrial structure and energy structure. Third, there are more studies based on urban panel data, and less analysis on a provincial scale. However, in the context of decentralization and government performance evaluation systems in China, competition, demonstration, and spatial correlation effects are more likely to occur among provinces (Zhang et al., 2011; Jacobsen et al., 2012; Lu & Zhang, 2016).

This paper aims to compensate for the above research deficiencies by building a comprehensive evaluation index of the digital economy and analyzing the impact mechanism of the digital economy on carbon emissions through technological and structural effects by using a spatial econometric model and panel data from 30 provinces in China from 2006 to 2020. Compared with the existing research, the possible marginal contributions of this paper are as follows. First, the digital economy is regarded as a comprehensive index covering digital technology, digital application, digital business, etc., and its impact on carbon emissions is investigated. Second, an impact mechanism model mediated by technological innovation and structural optimization is constructed to deeply analyze in-depth how the digital economy impacts carbon emissions. Third, the above mechanism is tested using provincial data from China, and a heterogeneity test of the development level of the digital economy is conducted to determine the difference in the impact of high- and low-level digital economies on carbon emissions.

## Theoretical Analysis and Research Hypotheses

The theoretical paths of the impact of the digital economy on regional carbon emissions are shown in Fig. 1.



**Fig. 1** Theoretical paths of the impact of the digital economy on regional carbon emissions

## The Impact of the Digital Economy on Regional Carbon Emissions

With the rapid development and widespread application of new technologies such as cloud computing, artificial intelligence, and the Internet of Things, the digital economy has had a significant positive effect on energy conservation, emission reduction, and green and high-quality economic development (Guo et al., 2023). The impact of the digital economy on carbon emission reduction is mainly reflected in three aspects: the digitalization of enterprise production, the intensification of product circulation, and the intelligence of social governance.

From the perspective of enterprise production digitalization, new digital technologies and deep digital practices can have scale, scope and long-tail effects (Xing et al., 2019). Through the digital integration of enterprise production, resource and transaction information, the allocation level of internal and external resources and elements can be improved, production costs and resource waste can be reduced, and green and low-carbon production can be promoted (Xu et al., 2019).

From the perspective of intensive product circulation, the development and wide application of intelligent logistics have led to a change in the distribution mode of the last kilometre of goods, from queuing purchases to centralized distribution. Research shows that during the last kilometre of delivery, the carbon emissions of goods account for approximately 28% of delivery process emissions. Due to economies of scale and scope, centralized distribution is much more efficient, and energy consumption and carbon emissions are far lower than those of decentralized purchases (Tiwari & Singh, 2011; Shao et al., 2016).

From the perspective of intelligent social governance, the government can use big data, cloud computing and other digital technologies to dynamically monitor and analyze environmental information and further strengthen the level of comprehensive ecological governance (Hampton et al., 2013; Shin & Choi, 2015). At the same time, the government can rely on digital platforms to build a three-way interactive environmental supervision bridge of government–enterprise–public (Yang et al., 2020) and realize information sharing through digital media, thus forming a new pattern of multientity environmental governance and promoting carbon emission reduction.

In addition, against the backdrop of decentralized fiscal incentives and official promotion incentives, “imitation” among local governments is widespread (Song et al., 2021). As a new model and business form of economic development, the digital economy and its related economic policies, industrial forms, and development models will radiate to surrounding areas due to imitation, competition, and correlation effects. Zhang et al. (2022) noted that the regional digital economy has both regional agglomeration and spatial spillover effects. Therefore, when examining the impact of the digital economy on carbon emissions, its spatial effects need to be included in the discussion framework. In summary, this paper proposes the following hypothesis:

**Hypothesis 1** The development of a digital economy is conducive to reducing regional carbon emissions, and the impact of the digital economy on regional carbon emissions has a spatial spillover effect.

## Analysis of the Impact Mechanism of the Digital Economy on Carbon Emissions

The literature indicates that technological innovation and structural effects are two important factors in reducing environmental pollution (Grossman & Krueger, 1995; Jalil & Feridun, 2011; Yang & Li, 2017), and the digital economy plays an important role in guiding technological innovation and promoting structural optimization (Xiao et al., 2023). Therefore, this study identifies the impact mechanism of the digital economy on carbon emissions from two dimensions: the effect of digital technology, which favours innovation, and the effect of digital structure, which favours application.

### Digital Economy, Technological Effects and Carbon Emissions

The impact of the digital economy on carbon emissions through technological innovation is mainly reflected in the following two aspects. First, according to Schumpeter's innovation theory, data, as a noncompetitive and nonexclusive new production factor, can promote knowledge spillover and information-sharing effects and expand the production possibility boundary while continuously extending the possibility boundary of innovation. Data-driven approaches promote innovation in green technology and energy-saving products, thereby reducing carbon emissions (Anderson, 2001; Yang & Jia, 2022).

Second, digital finance is an important application of the digital economy. On the one hand, introducing the environment, social responsibility and corporate governance (ESG) concept into the new development pattern of green finance can expand the coverage of green finance services, provide financial support for high-risk and high-cost green technology innovation, help enterprises ease the financing constraints of green innovation, and ensure the stability of green technology innovation output and the orientation of green and low-carbon output. On the other hand, using big data technology to carry out risk portraits of green financial entities and track the flow of financial resources weakens adverse selection and moral hazard and improves green financial resource efficiency. Moreover, data such as carbon footprint, carbon emission reduction and corporate portraits can be ecologically integrated with green financial products to enable green and low-carbon development (Zhang & Liu, 2022).

Accordingly, this paper proposes the following hypothesis:

**Hypothesis 2** The digital economy can reduce regional carbon emissions through technological innovation.

### Digital Economy, Structural Effects and Carbon Emissions

From the perspective of industrial structure, the change in the industrial structure of an economy has two main dimensions, namely, the rationalization of industrial structure and the upgrading of industrial structure.

First, the digital economy enhances the level of rationalization of the industrial structure. On the one hand, the digital economy can enhance the degree of coordina-

tion between industries. The fairness and interactivity of digital platforms enable both the supply and demand sides of elements to overcome the time and spatial barriers of information acquisition, reduce the cost of resource searches and the degree of element mismatch, achieve real-time two-way feedback and cloud sharing of information, and increase the level of coordination among industries (Huang & Chen, 2023). On the other hand, the digital economy can improve resource utilisation efficiency. An internet platform supported by the digital economy can intensify market competition, improve the efficiency of resource matching, optimize industrial specialization, alleviate regional resource mismatch and market distortion, break the flow barriers of production factors within a region, and coordinate the development of various industries (Zhang et al., 2022).

Second, the digital economy is conducive to upgrading the industrial structure. On the one hand, in the era of the digital economy, with the help of digital technologies and data elements, diversified emerging digital industries can be formed. The transformation of social productivity from manual and machine productivity to digital computing power can promote major changes in production relations and organizational patterns and help upgrade the industrial structure (Liu, 2022). On the other hand, with the rise of the Industrial internet, the development of industrial platformization and servitization has become increasingly prominent. Through innovation and optimization of the production organization, business management mode and business development mode, traditional industries continue to extend and upgrade the value chain and promote the industrial structure from a low-level structure dominated by labour- and capital-intensive industries to a high-level structure dominated by knowledge- and technology-intensive industries (Guan et al., 2022). Optimizing the industrial structure is conducive to reducing carbon emissions (Hu et al., 2020). Improving resource utilization efficiency, alleviating production element mismatches and increasing high value-added and low energy consumption enterprises brought about by industrial structure optimization are all conducive to reducing carbon emissions.

From the perspective of the energy structure, the digital economy has timeliness, permeability and externality, and its driving role in transforming the energy structure to low carbon has two dimensions, i.e., the energy production and energy consumption structures. First, the digital economy can optimize the energy production structure. On the one hand, energy digitization can improve the efficiency of traditional energy extraction, production, and transportation, reduce mining costs and energy losses, and improve energy production efficiency. For example, Shell collaborates with HP to transmit sensor data to proprietary servers through fibre optic cables and helps geologists make more accurate judgements about well locations by comparing potential oil field data with data from other oil fields worldwide, thereby improving energy production efficiency. On the other hand, digitalization has effectively stimulated the development of clean energy and enriched the clean energy categories, thus optimizing the energy structure and reducing carbon emissions (Wang et al., 2016; Zeng et al., 2023).

Second, the digital economy can optimize the energy consumption structure. On the one hand, digital technology can make the production process more digital and intelligent and reduce energy consumption and carbon emissions. For example,



introducing digital computing power and APC system optimization parameters in the Jidong Cement Plant in China reduced the standard coal consumption of clinker by more than 1 kg. On the other hand, digital technologies enable online, paperless lifestyles, thereby reducing the carbon footprint. For example, the shift of traditional shopping or meeting modes from offline to online can significantly reduce energy consumption and carbon emissions in individual transportation (Wang et al., 2016; Zeng et al., 2023).

Although the digital economy may reduce carbon emissions through the optimization effect of the energy structure while improving energy efficiency and reducing energy prices, it may also lead to synchronous growth in economic scale and energy consumption (Lange et al., 2020; Ren et al., 2021) through the energy rebound effect (Shao et al., 2013; Galvin, 2015). The income effect caused by the digital economy and the high dependence on traditional energy are important reasons for the energy rebound effect, which may have two types: direct and indirect rebound. Therefore, whether the digital economy can reduce regional carbon emissions through the optimization effect of the energy structure remains to be further tested.

Accordingly, this paper proposes the following hypothesis:

**Hypothesis 3** The digital economy can reduce regional carbon emissions through industrial structure optimization, but the impact mechanism of its energy structure optimization effect is uncertain.

## Models and Variables

### STIRPAT Model

The factor decomposition method is used to measure regional carbon emissions in China. The factor decomposition method was originally derived from the IPAT model proposed by Ehrlich and Holdren (1971), which uses multiplication to decompose factors affecting the environment into economic and social factors. The expression is  $I = PAT$ , where  $I$  denotes an environmental pressure or environmental factor,  $P$  denotes population factors,  $A$  denotes affluence factors, and  $T$  denotes technological factors. Dietz and Rosa (1994) improved the model and proposed the STIRPAT model, which has a wider range of applications and can be expressed as:

$$I_i = aP_i^b A_i^c T_i^d e_i \quad (1)$$

where  $a$  is the model coefficient;  $b$ ,  $c$  and  $d$  are the elasticity of population, affluence and technology on the environment, respectively; and  $e_i$  is a random perturbation term. In this paper, the STIRPAT model is transformed into a stochastic model used to test the impact of the digital economy on carbon emissions. In this model, carbon emissions are the environmental factor, the technology factor is replaced by the digital economy, GDP is the affluence factor, and population density is the population



factor. After taking the logarithm of both sides of the above equation, the following equation can be obtained:

$$\ln I_{it} = a + b \ln P_{it} + c \ln A_{it} + d \ln T_{it} + e_{it} \tag{2}$$

### Empirical Analysis Models

#### Spatial Spillover Models

Since both the digital economy and carbon emissions have spatial spillovers and the development of the digital economy is a continuous and dynamic process, the static spatial Durbin model (SDM) and dynamic spatial Durbin model (DSDM) are constructed for empirical analysis. The model is set as follows:

$$\begin{aligned} Carb_{it} = & \rho \sum_{j=1}^n w_{ij,t} Carb_{jt} + \tau \sum_{j=1}^n w_{ij,t} Dei_{jt} \\ & + \pi Dei_{it} + \psi X_{it} + v_i + \mu_t + \varepsilon_{it} \end{aligned} \tag{3}$$

$$\begin{aligned} Carb_{it} = & \rho \sum_{j=1}^n w_{ij,t} Carb_{jt} + \delta \sum_{j=1}^n w_{ij,t-1} Carb_{j,t-1} + \gamma Carb_{i,t-1} \\ & + \tau \sum_{j=1}^n w_{ij,t} Dei_{jt} + \pi Dei_{it} + \psi X_{it} + v_i + \mu_t + \varepsilon_{it} \end{aligned} \tag{4}$$

Equations (3) and (4) represent the SDM and DSDM, respectively, where,  $Carb_{it}$  and  $Carb_{jt}$  are the carbon emissions in regions  $i$  and  $j$  during period  $t$ , respectively;  $\rho$  and  $\delta$  are the spatial autocorrelation coefficient and spatial lag coefficient, respectively;  $Dei_{it}$  and  $Dei_{jt}$  are the development levels of the digital economy in regions  $i$  and  $j$  during period  $t$ , respectively;  $X_{it}$  is the control variable affecting carbon emissions in region  $i$  during period  $t$ ;  $\tau$ ,  $\pi$ ,  $\gamma$  and  $\psi$  are the model parameters to be estimated;  $v_i$  and  $\mu_t$  reflect the regional fixed effect and time fixed effect, respectively;  $\varepsilon_{it}$  is a random disturbance term; and  $w_{ij,t}$  is the element of the spatial weight matrix.

#### Mediation Effect Models

To further test the impact mechanism of the digital economy on carbon emissions, a regression model of the mediation effect is adopted, and three impact mechanisms are introduced: technological innovation, industrial structure and energy structure. The model is as follows:

$$Carb_{it} = \beta_0 + \theta_0 Dei_{it} + \psi_0 Z_{it} + \alpha_i + \omega_t + \epsilon_{it} \tag{5}$$

$$M_{it} = \beta_1 + \theta_1 Dei_{it} + \psi_1 Z_{it} + \alpha_i + \omega_i + \epsilon_{it} \tag{6}$$

$$Carb_{it} = \beta_2 + \theta_2 Dei_{it} + \theta_3 M_{it} + \psi_2 Z_{it} + \alpha_i + \omega_i + \epsilon_{it} \quad (7)$$

where  $M_{it}$  is an impact mechanism variable that reflects technological innovation, industrial structure optimization (including the rationalization of industrial structure and the upgrading of industrial structure) and energy structure optimization;  $Z_{it}$  represents the control variable;  $\psi_0$ ,  $\psi_1$  and  $\psi_2$  are the coefficients of the control variables;  $\theta_0$ ,  $\theta_1$ ,  $\theta_2$  and  $\theta_3$  are the model parameters to be estimated;  $\beta_0$ ,  $\beta_1$  and  $\beta_2$  are constant terms; and  $\alpha_i$ ,  $\omega_t$  and  $\epsilon_{it}$  are residual terms.

### Spatial Weight Matrices

The spatial spillover of carbon emissions is closely related not only to the geographical distance between individuals but also to the economic development level of different individuals. Therefore, the geographical distance weight matrix  $W_1$  and economic distance weight matrix  $W_2$  are constructed. The calculation formula for the element in matrix  $W_1$  is:

$$w_{ij,t} = \begin{cases} 1/d, & i = j \\ 0, & i \neq j \end{cases} \quad (8)$$

where  $d$  is the geographical distance between the capitals of provinces  $i$  and  $j$ . Referring to the method of Wang et al. [55], the calculation formula for the element in matrix  $W_2$  is:

$$w_{ij,t} = \begin{cases} 1/|x_{it} - x_{jt}|, & i \neq j \\ 0, & i = j \end{cases} \quad (9)$$

where  $x_{it}$  and  $x_{jt}$  are the GDP of provinces  $i$  and  $j$  during period  $t$ , respectively.

### Variables

#### Dependent Variable

The dependent variable is the per capita CO<sub>2</sub> emissions of each province. The data were sourced from the China Emission Accounts and Datasets (CEADs) from 2006 to 2020. The missing data were supplemented by the moving average method. In addition, ArcGIS software was used to analyze the spatial distribution of per capita CO<sub>2</sub> emissions in 30 provinces (excluding Tibet) in mainland China in 2006, 2010, 2015 and 2020, as shown in Fig. 2. Although the per capita CO<sub>2</sub> emissions of each province have changed over time, overall, the per capita CO<sub>2</sub> emissions are mainly concentrated in the relatively developed Beijing-Tianjin-Hebei region and coastal areas of central China, Xinjiang, which has a small population but is rich in resources, and Shanxi and Inner Mongolia, which have rich coal resources.

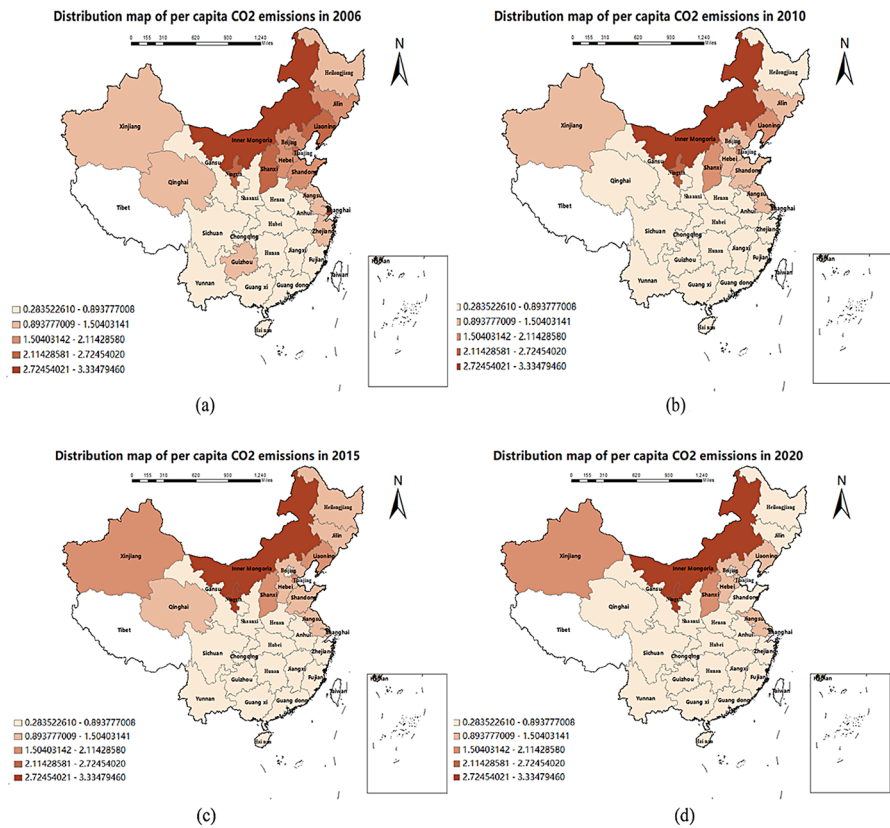
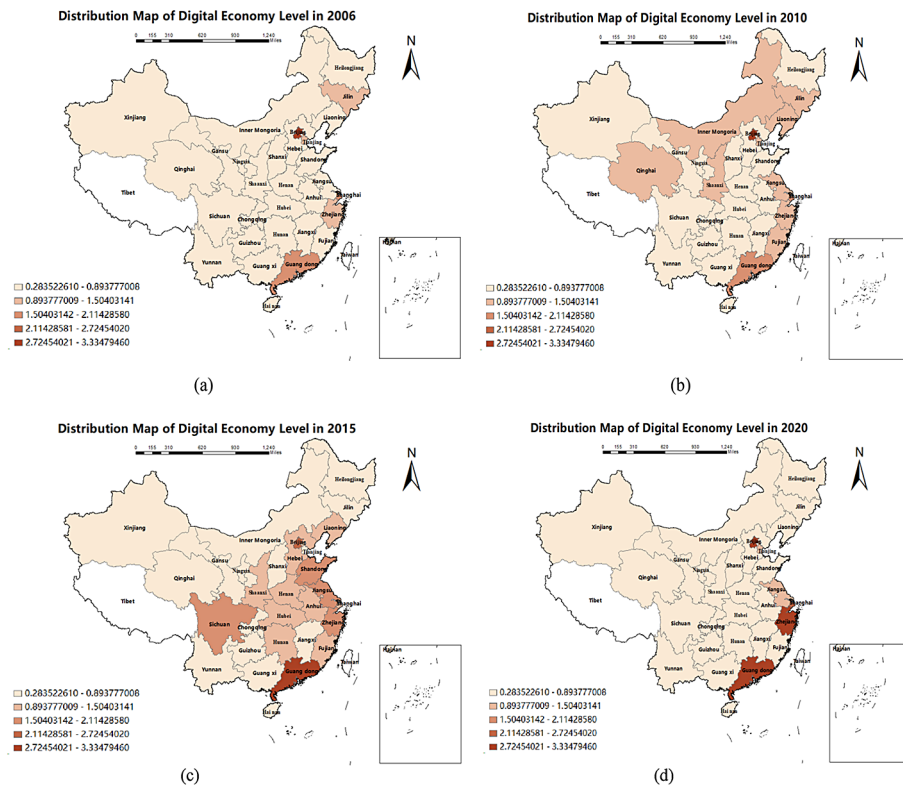


Fig. 2 The spatial distribution of per capita CO<sub>2</sub> emissions. (a) 2006. (b) 2010. (c) 2015. (d) 2020

### Core Explanatory Variable

The core explanatory variable is the development level of the digital economy. Referring to the method of Zhao et al. (2020), the development level of the digital economy is determined by integrating five indicators: internet penetration rate, relevant employees, relevant output, the mobile phone penetration rate, and digital finance development. The actual measurement variables corresponding to the above five indicators are the number of internet broadband access users per 100 people (Dong et al., 2022), the proportion of employment in computer services and the software industry in total employment (Yan & Zhang, 2023), the number of telecommunications services per capita (Li & Wang, 2022), the number of mobile phone users per 100 people (Yan et al., 2023), and the number of express services (Han et al., 2019), respectively. Using the principal component analysis method, dimensionality reduction is performed on the data of the above 5 indicators to eliminate their correlation, and the digital economy index of each province is calculated. Similar to per capita CO<sub>2</sub> emissions, ArcGIS software was used to analyze the spatial distribution of the digital economy index in 2006, 2010, 2015, and 2020, as shown in Fig. 3. Although



**Fig. 3** The spatial distribution of the digital economy index. (a) 2006. (b) 2010. (c) 2015. (d) 2020

the digital economy index value of each province has changed over time, overall, the regions with a higher level of digital economy development are mainly concentrated in the Beijing-Tianjin-Hebei region and the southeastern coastal areas, and high-high and low-low regional agglomeration effects have formed.

### Mechanism Variables

(1) Technological innovation. The existing research has mainly used the number of patents to measure technological innovation (Yan and Zhang., 2023; Zhao et al., 2023); thus, the number of patents per capita is used to measure the technological innovation level of each province.

(2) Industrial structure. Industrial structure variables include the upgrading and rationalization of the industrial structure. Many indicators measure the upgrading of the industrial structure. According to Clark's Law, many studies use the ratio of the sum of the GDP of the secondary and tertiary industries to total GDP to measure industrial structure upgrading. However, this method does not reflect the development trend of the industrial structure from low to high. Since the digital economy promotes the development of tertiary industry, which is dominated by the computer digital service and the data transmission and processing industries, the ratio of the

GDP of tertiary industry to the GDP of secondary industry is used to measure the level of upgrading of the industrial structure (Dong et al., 2022; Yan and Zhang., 2023). The higher the ratio, the more advanced the industrial structure. The rationalization level of the industrial structure is characterized by the reciprocal of the Theil index, as shown in Formula (9) (Wang et al., 2019). The larger the value, the more reasonable the industrial structure.

$$Ist = \frac{1}{\sum_{i=1}^3 (Y_i/Y) \ln \left( \frac{Y_i/Y}{L_i/L} \right)} \quad (9)$$

where  $i=1, 2$  and  $3$  represent the primary, secondary and tertiary industries, respectively;  $Y_i$  and  $L_i$  are the GDP and the employment of industry  $i$ , respectively; and  $Y$  and  $L$  are the total GDP and total employment, respectively.

(3) Energy structure. Energy is a crucial material foundation and driving force of economic and social development while also a primary battleground for achieving carbon peaking and neutrality. Among all energy sources, coal has consistently dominated carbon emissions (Song et al., 2023). Therefore, we represent the energy structure by the proportion of coal consumption to total energy consumption (Yan et al., 2023), which provides a deeper understanding of the overall impact on the energy structure. The lower the proportion, the more optimized the energy structure. The calculation formula is as follows:

$$Ens = \frac{Cc}{Ent} \quad (10)$$

where  $Cc$  represents coal consumption and  $Ent$  represents total energy consumption.

### Control Variables

The level of regional economic development is closely related to energy consumption and environmental pollution. A high or low level of regional economic development determines the foundation and limits of regional industrial development, thereby influencing carbon emissions. Therefore, we have chosen the level of economic development as a control variable, using GDP to characterize the level of economic development (Mi and Chang, 2017). Foreign direct investment (FDI) makes it easier for foreign companies to relocate their polluting enterprises to regions in China where the environmental standards are lower. This leads to an increase in carbon emissions in certain areas of China. Therefore, we selected the level of foreign investment as a control variable and used the total investment amount of foreign-invested enterprises to measure the level of foreign investment (Li & Wang, 2022). The population density directly influences the activity intensity of a region (Liu et al., 2017). A substantial population size provides a larger market for goods and services, consequently contributing to the rise in regional carbon emissions. Hence, we selected population density as a control variable, representing it as the ratio of the population of a province to its area (Zarco-Periñán et al., 2021).

We logarithmically transformed the independent variables to alleviate heteroscedasticity and endogeneity issues, excluding the digital economy index (DEI).

Table 1 shows the descriptive statistics of all variables from 2006 to 2020.

## Empirical Analysis

### Spatial Correlation test

Before conducting spatial econometric analysis on a certain indicator, it is necessary to use the global Moran's I index method to test whether there is spatial correlation. The calculation formula is as follows:

$$\text{Moran's I} = \frac{\sum_{i=1}^n \sum_{j=1}^n w_{ij} (Y_i - \bar{Y}) (Y_j - \bar{Y})}{S^2 \sum_{i=1}^n \sum_{j=1}^n W_{ij}} \quad (11)$$

where  $Y_i$  is the indicator value of region  $i$  and  $\bar{Y}$  and  $S^2$  are the mean and variance of the indicator, respectively, i.e.,  $\bar{Y} = \frac{\sum_{i=1}^n Y_i}{n}$ ,  $S^2 = \frac{\sum_{i=1}^n (Y_i - \bar{Y})^2}{n}$ .  $w_{ij}$  is the element of the spatial weight matrix.

**Table 1** The descriptive statistics of all variables

Variables	Variable name	Measure index	Symbol	Mean	St.Dev	Min	Max
Dependent variable	Carbon emissions	Per capita CO <sub>2</sub> emissions	<i>Carb</i>	7.719	5.137	2.059	35.717
Explanatory variable	development level of digital economy	Digital economy index	<i>Dei</i>	0	0.76	-0.956	4.361
Mechanism variables	Technological innovation	Number of patents granted per capita	<i>lnRzl</i>	1.397	1.281	-1.732	4.309
	Industrial structure	Upgrading level of industrial structure	<i>lnAis</i>	0.103	0.392	-0.640	1.657
		Rationalization level of industrial structure	<i>lnIsr</i>	1.738	0.825	0.160	4.841
	Energy structure	Proportion of coal consumption	<i>lnEns</i>	-0.983	0.549	-4.547	-0.291
control variables	Economic development	GDP	<i>lnGDP</i>	9.266	0.966	6.372	11.32
	Population	Population density	<i>lnPeo</i>	5.450	1.285	2.026	8.275
	Foreign investment	Foreign investment in actual use	<i>lnFDI</i>	10.967	1.465	7.601	14.8

The spatial weight matrix of economic distance is selected to obtain the global Moran's I index values of carbon emissions and the digital economy development index of 30 provinces from 2006 to 2020, and the results are shown in Table 2.

All the global Moran's I index values are significantly positive at the 1% significance level, indicating that both carbon emissions and the DEDI have positive spatial correlations and are suitable for spatial econometric analysis.

## Results and Analysis

### Analysis of Regression Results of Benchmark Models

After the LM test and Hausman test, a spatiotemporal dual fixed SDM is determined. In Table 3, Column (1) gives the OLS regression results without adding independent variables, while Columns (2) — (5) give the full sample regression results under two spatial weight matrices. It can be seen that the degree of dynamic SDM (DSDM) is a better fit. The results in Columns (1) — (5) show that the coefficients of the digital economy development index are all negative and significant at the 1% level, indicating that the development of the provincial digital economy can significantly curb carbon emissions.

The spatial autoregressive coefficients in Columns (3) and (5) are 1.344 and 0.336, respectively, and the coefficients of the carbon emission lag term are 0.859 and 0.917, respectively, which pass the significance test of 1%, indicating that provincial carbon emissions spill over space and lag in time; that is, Hypothesis 1 is verified. In terms of both temporal and spatial dimensions, the coefficients of the spatiotemporal lagged terms for per capita carbon dioxide emissions under the economic distance matrix and geographic distance matrix are significantly positive. This indicates that higher per capita carbon dioxide emissions in the previous period in a given region have a promoting effect on per capita carbon dioxide emissions in neighbouring regions, suggesting a spatiotemporal monsoon effect.

**Table 2** Global Moran's I index values

Year	Carb		Dei	
	Moran's I	Z value	Moran's I	Z value
2006	0.141***	5.318	0.185***	8.122
2007	0.121***	4.831	0.194***	8.503
2008	0.199***	4.340	0.213***	9.687
2009	0.186***	3.942	0.209***	9.366
2010	0.188***	3.986	0.207***	9.461
2011	0.154***	3.007	0.187***	8.526
2012	0.162***	3.274	0.188***	8.678
2013	0.170***	3.368	0.205***	9.381
2014	0.172***	3.373	0.193***	8.896
2015	0.165***	3.209	0.157***	5.532
2016	0.166***	3.248	0.207***	9.192
2017	0.147***	2.645	0.211***	9.198
2018	0.155***	2.946	0.213***	9.108
2019	0.148***	2.723	0.214***	9.085
2020	0.144***	2.623	0.212***	8.872



**Table 3** Regression results of the models

Variables	(1)	(2)	(3)	(4)	(5)
	OLS	economic distance weight matrix		geographical distance weight matrix	
		SDM	DSDM	SDM	DSDM
<i>Carb</i> <sub>t-1</sub>			0.859***		0.917***
<i>W</i> × <i>ln</i>			(31.14)		(37.09)
<i>Carb</i> <sub>t-1</sub>			0.056*		0.206***
			(1.83)		(2.67)
<i>Dei</i>	-0.427***	-0.527***	-0.436***	-	-
	(-2.78)	(-4.65)	(-2.89)	0.685***	0.563***
				(-2.87)	(-4.31)
<i>lnAis</i>		-1.325***	-2.254***	-	-
				3.416***	2.354***
				(-3.59)	(-4.21)
<i>lnIsr</i>		1.32**	-0.735***	-	-
				1.074***	0.824***
				(-3.66)	(-4.63)
<i>lnEns</i>		0.073***	0.258**	4.462***	1.625***
				(11.86)	(6.25)
<i>lnRzl</i>		-0.057***	-0.241***	0.086	-
					0.060***
				(0.26)	(-3.06)
<i>lnGDP</i>	1.305***	-0.015	0.957**	1.210*	0.956***
	(2.67)	(-0.52)	(2.39q)	(1.95)	(2.79)
<i>lnFDI</i>	0.302*	-0.361***	-0.369**	-0.004*	-0.129*
	(1.85)	(-2.98)	(-2.23)	(-1.74)	(-1.92)
<i>lnPeo</i>	0.021**	-0.006***	-0.012***	-	-0.001
				0.003***	
	(2.23)	(-4.62)	(-3.71)	(-5.10)	(-0.81)
<i>W</i> × <i>lnDei</i>		-4.602***	-2.248***	-	-
<i>W</i> × <i>lnAis</i>		(-3.68)	(-2.79)	0.384***	8.309***
<i>W</i> × <i>lnIsr</i>		14.333*	-1.615***	(-5.10)	(-10.30)
<i>W</i> × <i>lnEns</i>		(1.88)	(-3.35)	-18.857*	-6.875**
<i>W</i> × <i>lnRzl</i>		-8.459	-4.310**	(-2.32)	(-2.51)
<i>W</i> × <i>lnGDP</i>		(-1.32)	(-2.48)	-4.041*	0.014***
<i>W</i> × <i>lnFDI</i>		5.357	2.157**	(-1.89)	(5.05)
<i>W</i> × <i>lnPeo</i>		(0.35)	(2.56)	4.736*	-
		-0.487	3.369***	(1.94)	0.293***
		(-0.87)	(2.97)	1.739	(-4.75)
		24.720**	-21.045*	(0.55)	-1.471*
		(2.48)	(-1.86)	-32.237*	(-1.78)
		-9.590**	-1.430	(-1.98)	-
		(-0.76)	(-1.64)	0.647†	6.852***
		9.009	-5.468**	(1.89)	(-4.26)
		(0.76)	(-2.53)	-8.755	0.083***
				(-1.45)	(3.47)
					-11.882*
					(-1.97)
$\rho$		0.842***	1.344***	0.085***	0.366***
		(2.79)	(5.36)	(3.28)	(4.97)
R <sup>2</sup>	0.016	0.254	0.952	0.056	0.833

In addition, after considering the time–space lag factor, economic development will increase per capita carbon emissions, indicating that the expansion of economic scale is one of the important factors for the increase in carbon emissions. Population density and foreign investment can reduce carbon emissions somewhat, indicating that a population increase will not lead to an increase in per capita carbon emissions, and an increase in FDI can restrain the rapid growth of carbon emissions, making an important contribution to low-carbon and high-quality economic development.

### Decomposition Analysis of Spatial Effects

To test the marginal effect of the explanatory variable on the dependent variable, the partial differential method is used to decompose the impact of digital economy development on carbon emissions into three dimensions: direct, indirect, and total effects (Pace & Lesage, 2009). Due to the inclusion of time lag and spatiotemporal lag coefficients in the dynamic spatial Durbin model (DSDM), in the temporal dimension, direct, indirect, and total effects can be further divided into short- and long-term effects. This allows the reflection of the immediate short-term impacts of various influencing factors on carbon emissions and considers time-lagged long-term effects (Z., 2023). Table 4 shows the long- and short-term effects of the dynamic spatial Durbin model based on the economic distance weight matrix. In the short term, the development of the digital economy has a significant inhibitory effect on carbon emissions, including direct effects (-0.1.28), indirect effects (-13.538), and total effects (-14.818). This means that improving the digital economy in a province can not only reduce the carbon emissions of that province but also inhibits carbon emissions of the surrounding provinces.

The carbon reduction effect of the digital economy has spatial spillover effects for two main reasons. First, the development of the digital economy in a region can pro-

**Table 4** Decomposition of direct, indirect and total effects of DSDM

Variable	short-term effect			long-term effect		
	direct	indirect	total	direct	indirect	Total
<i>Dei</i>	-1.28* (-1.83)	-13.538*** (-5.94)	-14.818** (-2.07)	-0.875* (-1.97)	-2.657 (-0.11)	-3.532*** (-3.33)
<i>lnAis</i>	-3.637*** (-2.52)	-2.093** (-2.45)	-5.730*** (-3.18)	-2.687 (1.13)	5.821* (-1.80)	3.134 (-1.56)
<i>lnIsr</i>	-1.016 (-1.18)	-1.913 (-0.99)	-3.073** (-2.23)	-0.0784** (-2.04)	-1.489 (-0.79)	-2.273** (-2.39)
<i>lnEns</i>	0.597*** (2.97)	0.465* (1.77)	1.062* (1.85)	3.130 (0.46)	-0.896 (-0.05)	2.234 (0.84)
<i>lnRzl</i>	0.007 (0.720)	0.051 (0.92)	0.058** (2.43)	0.020** (3.12)	0.002 (0.08)	0.022 (0.78)
<i>lnGDP</i>	1.640* (-1.74)	6.344** (-2.31)	7.984** (-2.35)	-0.684 (-1.41)	1.278 (0.72)	0.595** (2.54)
<i>lnFDI</i>	1.251*** (2.61)	1.233 (0.32)	2.484** (2.47)	-0.098* (-1.66)	-0.171 (-0.43)	-0.269 (-0.68)
<i>lnPeo</i>	-0.085 (-0.22)	-0.004* (-1.96)	-0.089* (-1.95)	0.000 (0.08)	0.003* (1.65)	0.003 (1.57)

mote rapid socioeconomic development and industrial scale expansion, promoting talent aggregation, infrastructure improvement, and stable development of the market economy. Under the condition that the total social investment remains unchanged in the short term, due to the “siphon effect” and “beggar-thy-neighbour effect”, the economic development of the surrounding areas is relatively slow, inhibiting energy consumption and the economic development speed of the surrounding areas, further reducing carbon emissions (Peng et al., 2022). Second, under China’s decentralized promotion and incentive system, regional economic policies and innovative technologies are affected by the spatial “demonstration effect” and “competition effect”, resulting in competition and imitation learning between local and neighbouring regions (Song et al., 2021). Thus, the development path of the digital economy and the effect of carbon emission reduction in this region have spatial transmission and spillover effects on surrounding areas. In the long run, the direct and indirect effects of the digital economy are not significant, but the total effect is significant. The possible reason is that the digital economy is still in the development stage, and long-term effects on the surrounding areas have not yet formed.

### Mechanism Effect test

(1) Technical effect. Column (1) in Table 5 shows the empirical results of the impact of the digital economy on carbon emissions through the effect of technological innovation. The results show that the digital economy significantly improves the level of technological innovation and, thus, can significantly reduce carbon emissions through technological innovation. At the same time, the digital economy coefficient becomes less significant after the addition of the mechanism variable, indicating that technological innovation plays a complete mediating role.

In the past, the long-term local protectionism and information transmission barriers made it difficult for production elements, innovation resources and talent to freely flow across regions, departments and industries. After China entered a new stage of high-quality economic development, the digital economy with big data and the Internet of Things as the core released the magnification, superposition and multiplication of knowledge flow and information spillover. As a result, technology spillovers and innovation synergies can be generated through various links, such as production, circulation and exchange, leading to technological model and mechanism innovation and assisting in energy conservation and emission reduction. This is consistent with the research results of Ma et al. (Ma et al., 2022); thus, Hypothesis 2 has been verified.

(2) Structural effects. Columns (2) and (3) in Table 5 show the regression results for the upgrading and rationalization of the industrial structure. The digital economy can significantly promote the advancement and rationalization of the industrial structure. Table 6 shows the bootstrap test results for upgrading the industrial structure. The indirect effect is significant for 5000 samples, indicating that the upgrading of the industrial structure plays a mediating role. After the industrial structure is rationalized, the impact of the digital economy on per capita CO<sub>2</sub> emissions is no longer significant; thus, the rationalization level of the industrial structure plays a complete mediating role. While the industrial policy system has continuously improved, the

**Table 5** The results of mechanism effects

Variable	(1)		(2)		(3)		(4)		(5)
	lnRzl	Carb	lnAis	Carb	lnIsr	Carb	lnEns	Carb	Gax
<i>Dei</i>	6.234*** (8.74)	-0.329 (-0.87)	1.036*** (11.45)	-0.447*** (-2.76)	3.297*** (9.84)	-1.594 (-0.44)	- 0.011*** (-13.21)	-0.316** (2.23)	2.516*** (7.93)
<i>lnRzl</i>		-0.152** (-2.44)							
<i>lnAis</i>				-0.271 (-0.68)					
<i>lnIsr</i>						-0.105** (-2.43)			
<i>lnEns</i>								2.305*** (4.45)	
Constant	-12.315 (-0.77)	13.267*** (4.38)	4.548*** (15.36)	17.541*** (19.21)	8.906*** (2.84)	19.652** (2.35)	0.625*** (4.59)	12.647*** (6.33)	7.681*** (5.62)
Control variables	YES	YES	YES	YES	YES	YES	YES	YES	NO

**Table 6** Bootstrap test results

Variable	Effect	Coef.	Std. Err.	$P> Z $	LLCI	ULCI
<i>Ais</i>	Indirect	1.364	0.458	0.002	0.254	1.763
	Direct	2.851	0.728	0.157	-0.376	1.624

digital economy has incubated emerging technology industries and the green and low-carbon transformation of traditional industries, upgraded and rationalized the industrial structure, and achieved the “double carbon” goal.

The Column (4) results show that increasing the proportion of coal energy consumption can significantly increase per capita CO<sub>2</sub> emissions. Improving the digital economy can significantly reduce the proportion of coal energy consumption; that is, it can play a role in optimizing the energy structure, but the impact is small (the coefficient is only -0.009). Moreover, after adding the mechanism variable, the coefficient of the digital economy is still significant, indicating that the energy structure only has a partial mediation effect.

Since natural gas is regarded as a clean energy, the impact of the digital economy on natural gas (*Gax*) is analysed, and the regression results are shown in Column (5). The digital economy can significantly increase the consumption of natural gas. According to the above results, on the one hand, the development and application of the digital economy can increase the demand and consumption of clean energy and reduce energy consumption by improving resource allocation and utilization efficiency of production factors. On the other hand, transforming the digital economy has driven an increase in total economic output, resulting in an increase in energy consumption, including traditional fossil fuels, thus leading to an energy rebound effect. In other words, while digital economy reform significantly increases the consumption of natural gas, it also increases the consumption of traditional energy sources, such as coal and oil, so that this rebound partially offsets the optimization effect of the energy structure. Therefore, Hypothesis 3 is only partially supported.

## Further Analysis

### Instrumental Variable Method

Endogenous mitigation is an important economic issue. While developing the digital economy may lead to a reduction in carbon emissions, the policy requirements of low-carbon emission reduction promotes digital industry development with high added value and low energy consumption. Therefore, there may be a certain two-way causal relationship between them. To solve the endogeneity problem of the core explanatory variable and the possible two-way causal problem in the empirical study, the historical data of posts and telecommunications in each province in 1984 are selected as the instrumental variable of the digital economy index, and the instrumental variable regression method is used for testing. On the one hand, the post office is an information and communication hub and external communication mode in the early stage of local economic development. With respect to infrastructure construction, postal and telecommunications departments can affect the layout of the internet and the development of the digital economy in the later stage. On the other hand, it is difficult for the historical number of post offices to affect current carbon emissions and satisfy the exclusivity hypothesis. In addition, since the research sample is panel data, the interaction terms between the number of post offices per million people in each province in 1984 and the national internet investment in the previous year are constructed using the methods of Nunn and Qian (2014), and logarithmic processing is performed as an instrumental variable (*Iv*) of the digital economy index of each province. Table 7 shows the results of the instrumental variable regression. The Kleibergen–Paap rk LM statistics and the Cragg–Donald Wald F test show that there is no problem with the insufficient identification of instrumental variables and weak instrumental variables. As shown in the regression results of the instrumental variables in Columns (1)–(4) of Table 7, the digital economy has a negative impact

**Table 7** Instrumental variable regression results

Primary variable	(1)		(2)		(3)		(4)	
	2SLS		2SLS		2SLS		2SLS	
	First stage	Second stage	First stage	Second stage	First stage	Second stage	First stage	Second stage
	Dei	Carb	Dei	Carb	Dei	Carb	Dei	Carb
<i>Dei</i>		-2.707*** (-4.33)		-3.927*** (-6.520)				
<i>Iv</i>	0.001*** (13.050)		0.001*** (8.110)					
$\rho$								
Kleibergen–Paap rk LM		108.397***		51.128***				
Cragg–Donald Wald F		135.368***		56.450***				
Control variables	NO	NO	YES	YES				
Constant	-7.626*** (-13.490)	7.719*** (0.640)	-4.819*** (-12.260)	34.799*** (7.37)				

on carbon emissions, which is consistent with the previous benchmark regression results, indicating that the conclusion is robust.

### Heterogeneity Analysis

China has a vast territory, and there are great regional differences in economic foundation and cultural heritage. Is the emission reduction effect of the digital economy the same across China's provinces in different regions? To this end, regression is carried out for the subregions. Columns (1)–(3) in Table 8 show the results of regional heterogeneity based on the DSDM. Compared with the digital economy coefficient of the eastern province, which is  $-0.254$  and significantly negative at the 1% level, the digital economy coefficient of the western region is only  $-0.142$ . The digital economy has an inhibitory effect on carbon emissions in both the eastern and western provinces, and the carbon emission reduction effect of the digital economy in the eastern region is more significant. The coefficient of the digital economy in the central region is positive, indicating that developing the digital economy in the central provinces will increase local carbon emissions. The central region is rich in mineral resources, and the economic development of the provinces in this region is highly dependent on traditional resources. As a result, path dependence and lock-in effects on local natural resource endowments and traditional industrial structures will be generated, restricting technological and structural effects and reducing the significance of the effect of the digital economy on carbon emissions in the central region. This also somewhat proves the existence of the “resource curse hypothesis”. The digital economy's income and energy rebound effects will further increase the carbon dioxide emitted by the central provinces.

To explore the differences in the effects of different digital economy development levels on carbon emission reduction, provinces are divided into high- and low-level digital economy development regions based on the average value of the digital economy index. According to Columns (4) and (5) in Table 8, digital economy development always plays an inhibitory role in regional carbon emission reduction under different levels of digital economy development. Moreover, the inhibitory effect is more significant in provinces with a high level of digital economy development.

### Conclusion and Suggestions

Based on the panel data of 30 provinces in China from 2006 to 2020, this paper explores the impact of digital economy development on provincial carbon emissions in China and its mechanism. The conclusions show that (1) both the digital economy and carbon emissions have obvious regional agglomeration characteristics, showing a significant positive spatial correlation; (2) overall, the development of the digital economy can reduce provincial carbon emissions and has a “local-neighbourhood” effect; that is, the carbon emission reduction effect of the digital economy has spatial spillover to the surrounding areas. (3) The digital economy can exert its inhibiting effect on carbon emissions by promoting regional technological innovation and improving the rationalization and upgrading of industrial structure, while the mediat-

**Table 8** Additional regression results

Variable	(1)	(2)	(3)	(4)	(5)
	Eastern	Central	Western	High-level	Low-level
$Carb_{t-1}$	0.621*** (8.21)	0.463*** (6.53)	0.806*** (11.85)	0.782*** (20.14)	0.862*** (34.45)
$W \times \ln Carb_{t-1}$	0.023** (2.30)	0.014* (1.89)	0.038 (0.45)	-0.033 (-0.66)	0.067** (1.79)
$Dei$	-0.254*** (-5.26)	0.287 (0.98)	-0.142 (-0.44)	-0.368** (-2.25)	-0.226 (-1.51)
$W \times Dei$	-0.348 (-0.37)	-1.124 (-0.52)	-2.325 (0.17)	-0.554 (-0.45)	-0.768 (-0.76)
$\rho$	0.326** (2.48)	0.720*** (5.67)	0.843* (1.78)	0.586* (1.84)	0.809*** (18.64)
Control variables	YES	YES	YES	YES	YES
Mechanism variables	YES	YES	YES	YES	YES
$R^2$	0.931	0.822	0.894	0.906	0.865

ing effect of energy structure optimization is not significant. (4) The impact of the development of a digital economy on carbon emissions in China's eastern, central, and western regions is regionally heterogeneous. Unlike in the eastern and western regions, carbon emissions in the central region will increase due to the development of the digital economy. In addition, different levels of the digital economy will have an inhibitory effect on carbon emissions, and the effect of high-level digital economy development areas is significantly greater than that of low-level areas.

This paper provides a theoretical basis for clarifying the relationship between the digital economy and regional carbon emissions and formulating a series of policies to promote green and low-carbon digitization. First, the Chinese government should start from the top-level design and pay attention to the overall layout of the digital economic development circle. Although under the fiscal decentralization system, local governments have formed a competitive mode of economic development in their jurisdiction based on a "competition for growth" model, they often fall into the dilemma of "beggar-thy-neighbour". Therefore, governments should pay attention to the spatial spillover effect and ensure relatively centralized overall deployment of the regional distribution of digital economy development and key development areas to form healthy competitive and cooperative relationships between neighbouring regions. At the same time, it is necessary to strengthen interregional learning and exchange of low-carbon technologies and green industries and build a characteristic digital economy and low-carbon economy model with good spatial effects. Second, the government should take the initiative to embrace digital economy platforms, accelerate digital technology innovation, promote optimizing and upgrading the industrial structure, and actively build new energy storage and consumption systems. Although the digital economy has penetrated all aspects of production and life, how the government can use it to "boost" green and low-carbon development continues to be a major challenge. Therefore, governments should strengthen the introduction of



talent and incentives for technological innovation and promote the optimization of industrial structure with an increase in innovation. At the same time, the construction of clean energy infrastructure and the enrichment of application scenarios should be accelerated, the rebound shackles of energy structure optimization should be lifted, and the digital economy should better support low-carbon and green development. Third, the government should improve the regional applicability of digital policies and regional flexibility of emission reduction initiatives based on local conditions. The eastern region should continue to promote the development of the digital economy. The western region should seize the development opportunity of “counting in the east and counting in the west”, take advantage of its vast land area and abundant clean energy resources, promote the coordinated development of the east and the west, and achieve carbon reduction and energy structure transformation. While developing the digital economy, the central region should promote diversifying the energy structure and constructing digitally active power grids, introduce green power from outside the region, promote zero-carbon emission demonstration projects, enhance the ecological carbon sink capacity, break the path dependence and lock-in effect of inherent resource endowment and traditional industrial structure, and reduce carbon emissions.

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**Consent to Participate** Not applicable.

**Consent for Publication** Not applicable.

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