



The nonlinear effects of digital economy on the low-carbon green total factor productivity: Evidence from China

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Abstract

The production process has undergone significant changes due to the exponential expansion of digital economy, leading to implications for carbon emissions. This study aims to establish the digital economy (DE) index and measures low-carbon green total factor productivity (CTFP) in 30 Chinese provinces between 2011 and 2020. Utilizing the panel fixed-effects model and the spatial model, it examines the nonlinear effects of DE on CTFP and investigates its underlying mechanism. The results reveal the following findings: (1) CTFP has experienced a decline over the past decade, while DE has exhibited significant growth. (2) the contribution of DE to CTFP follows a U-shaped pattern, indicating that CTFP experiences a significant increase once DE reaches a specific turning point. (3) DE affects CTFP by influencing technological innovation progress. (4) The impact of DE on CTFP exhibits regional heterogeneity, with the eastern region experiencing a spatial spillover effect. These rigorous empirical findings provide valuable insights for national policymakers, emphasizing the importance of prioritizing the digital economy and technological innovation when formulating policies to facilitate sustainable economic growth and reduce carbon emissions.

Keywords Digital economy · Low-carbon green total factor productivity · Technological innovation · Carbon emission · Nonlinear effect · Spatial spillover effect

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Highlights

- This study reveals a decline in low-carbon green total factor productivity (CTFP) over the past decade.
- The research establishes the U-shaped nonlinear effects of the digital economy on CTFP.
- It demonstrates that the digital economy impacts CTFP through technological innovation progress.
- Regional heterogeneity is observed in promoting the digital economy on CTFP, particularly in the eastern and high GDP regions. Additionally, a spatial spillover effect is found in the eastern region.

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Introduction

In recent decades, China has witnessed significant economic growth; however, the rapid growth has been accompanied by high pollution levels. (Zhou and Tang 2022). According to the EPS database, China's coal consumption reached 4.675 billion short tons in 2021, accounting for 54.52% of the total energy consumed globally by countries. Despite China's GDP being \$17.7 trillion, representing only 18.5% of the world's share, its carbon emissions reached a staggering 33.884 billion tons, ranking first worldwide. The expansion of the global economy has consequently brought about the emission of greenhouse gases, notably carbon dioxide, and has given rise to severe environmental challenges. Recognizing these concerns, the Chinese government officials pledged to achieve a "carbon peak" and "carbon neutrality" during the 75th session of the United Nations General Assembly, emphasizing the importance of sustainable development. Consequently, striking a balance between environmental preservation and economic growth and finding solutions to curb excessive carbon emissions has become an urgent priority for China. Numerous scholars

have researched and proposed potential solutions to address the issue of excessive carbon emissions. These solutions include the implementation of low-carbon energy generation policies (Tong et al. 2018), the promotion of coal power generation efficiency (Mohsin et al. 2021), the regulation of energy consumption structures (Valadkhani et al. 2019), and the increased utilization of renewable energy sources (Godil et al. 2021).

However, the primary concern is finding ways to reduce carbon emissions and sustain economic growth simultaneously. Digitalization has emerged as a promising trend for the future, with DE playing an indispensable role in economic development. The concept of the digital economy encompasses integrating intellectual capital, information, and creativity to drive progress, generate income, and advance society (Mankiw et al. 1992). On the one hand, adopting DE offers environmental benefits by utilizing fewer resources and producing less pollution. These inherent characteristics enable DE to break away from the traditional economic expansion paradigm, which is associated with elevated pollution levels and excessive energy consumption (Luo et al. 2022). On the other hand, DE accelerates economic growth and necessitates a reconstructing financial management framework. Internet technology has dismantled the limitations imposed by conventional geographic boundaries, reducing both the spatial and temporal gaps between locations and enhancing resource integration (Ren et al. 2021). Therefore, governments must consider the influence of DE on carbon emissions and foster regional cooperation to achieve the goals of "peak carbon" and "carbon neutrality" (Li and Wang 2022).

Scholars have researched DE and carbon emissions from various perspectives. Some studies have directly analyzed the influence of DE on carbon emissions (Wang et al. 2022a). In contrast, others have explored DE's impact on energy development (Chen 2022) or electricity intensity (Lin and Huang 2023), a significant carbon emission source. However, there is a research gap that considers both reducing carbon emissions and economic development. To achieve high-quality economic growth with low carbon emissions, finding an indicator that reflects both economic performance and emissions is essential factor productivity (GTFP) serves as such an indicator as it can balance environmental pollution and economic growth. GTFP considers both pollution emissions and economic growth as output indicators, where economic growth is expected, and pollution is considered unexpected. Building upon GTFP, low-carbon total factor productivity (CTFP) incorporates carbon emissions as the measure of pollution (Gao et al. 2021). CTFP can be utilized as a metric to assess the stage of China's low-carbon economy's growth (Wang et al. 2022b). It is particularly suitable for research examining economy development and carbon emissions.

The coexistence of economic growth and carbon reduction motivates us to analyze the impact of DE on CTFP. Understanding the relationship or the underlying influence rules between DE and CTFP can assist governments in formulating appropriate policies and efforts to enhance DE while simultaneously reducing carbon emissions. With this in mind, we pose the following research questions: (1) Does DE promote CTFP? (2) If there is a positive effect, what is the transmission mechanism behind it? (3) Does this effect vary across different regions? To address these questions, we first measure the CTFP of 30 Chinese provinces, considering carbon emissions as the only unexpected output. Once the measurement is complete, we employ models to investigate the relationship between DE and CTFP. Our analysis aims to uncover the mechanisms through which DE influences CTFP and determine whether there are regional variations in this relationship.

This study has several significant contributions. Firstly, it measures the CTFP of 30 Chinese provinces, which has practical implications for policymakers. CTFP is an accurate indicator to illustrate the relationship between economic growth and carbon emissions. Secondly, it uncovers the impact of DE on CTFP and identifies regional heterogeneity in this relationship. By revealing the effect of DE on CTFP, the study offers a new perspective and approach to achieving reduction. Lastly, it explores the transmission mechanism between DE and CTFP, providing insight into the growth of digital economy. The empirical results provide robust evidence for national policymakers, emphasizing the importance of considering DE when formulating policies to achieve high-quality economic growth and carbon emissions reduction.

The main contents of the following sections are as follows. "Literature review and hypothesis development" section provides an overview of the literature and establishes the hypotheses. In "Models established" section, the model employed in this study is introduced. "Variable selection" section measures the DE and CTFP indexes in China and explains the other variables and data sources. "Results and discussion" section shows the empirical results. "Conclusions and policy suggestions" section concludes and draws the policy proposal. The logic and structure of this research are shown in Fig. 1.

Literature review and hypothesis development

From an economic standpoint, scholars argue that DE significantly correlates with economic progress (Li et al. 2020; Wang et al. 2022c). This is because DE reduces the spatial and temporal separation between locations and facilitates resource integration. More specifically,

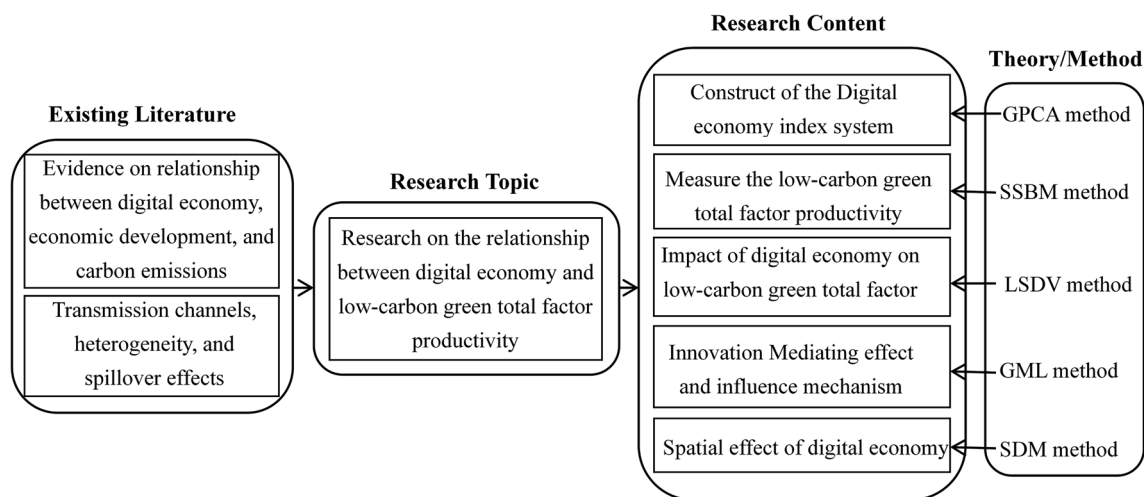


Fig. 1 Theoretical framework

DE promotes total factor productivity in industrial processes by enhancing services and fostering innovation capital (Wen et al. 2022). From an environmental perspective, DE has the potential to reduce carbon emissions and also improve energy efficiency directly (Zhang et al. 2022). Additionally, DE has been found to enhance energy efficiency significantly, and its positive effect on energy efficiency tends to increase as the level of economic development rises (Wang and Shao 2023). From both economic and environmental standpoints, DE has an impact on GTFP, and these benefits can be attributed to the promotion of green technological advancements (Lyu et al. 2023).

For the transmission channels technological innovation and efficiency are recognized as essential transmission channels that support economic growth (Romer 1986; Mankiw et al. 1992). DE directly stimulates high-quality economic growth and indirectly contributes to it through the development of green technologies (Ma and Zhu 2022), promotion of green technology innovation (Guo et al. 2023), and fostering entrepreneurial activity (Zhao et al. 2023). DE has the potential to directly reduce carbon emissions and indirectly by driving green innovation, reducing the reliance on fossil fuels (Wang et al. 2022b), advancing technical innovation, and optimizing industrial structures (Cheng et al. 2023).

The relationship between economy and the environment frequently demonstrates a non-linear effect. For instance, the relationship between the economy's transition to green development and its impact on carbon emissions is characterized by a non-linear pattern with a threshold (Zhou and Tang 2022). Similarly, the intensity of electricity usage has been discovered to follow an inverted U-shaped effect on technological improvement (Lin and Huang 2023). Moreover, researchers have found that DE has U-shaped non-linear

regional spillover effects on both carbon emissions and GTFP (Cheng et al. 2023).

There are spatial spillover effects on industrial transformation (Zhanbayev and Bu 2023), government support (Liang and Li 2023), and carbon reduction (Yi et al. 2022) when DE is conducted as the independent variable. Furthermore, it is crucial to acknowledge the heterogeneous nature of the spillover effect in different regions (Deng et al. 2022), highlighting the importance of accounting for spatial spillover effects and heterogeneity in our study.

Generally, many scholars researched to examine the influence of DE on total factor productivity, carbon emission, and energy efficiency. However, there are still some gaps in the existing literature. Firstly, considering that carbon emissions and economic growth play a crucial role in balancing social development, it is worthwhile to analyze the relationship between DE and CTFP. Secondly, the impact of DE on carbon emissions remains a topic of controversy. Hence, it is necessary to thoroughly investigate the relationship between DE and CTFP since it can reveal the inherent contradiction between economic development and carbon emissions. Lastly, the internal mechanism of DE and CTFP remains unclear. Further research is needed to better understand and explain the intricate mechanisms.

We believe that more significant carbon emissions stand for smaller CTFP when all other factors are equal, with CO₂ as the only unexpected output. To determine the appropriate non-linear model for our research, we conducted a scatter plot analysis of DE and CTFP, revealing a U-shaped pattern (Fig. 2).

During the initial stage of DE development, a great deal of labor, capital, and energy is consumed for infrastructure construction. This primary stage of DE differs from the mature period, suggesting a non-linear influence of DE on

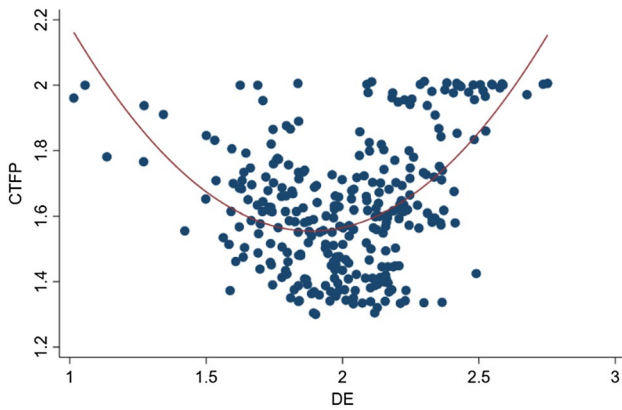


Fig. 2 The relationship between DE and CTFP

CTFP. Based on previous research and theoretical analysis, we put forth hypothesis 1.

Hypothesis 1: The effect of DE on CTFP exhibits a U-shaped nonlinear relationship.

Referring to the literature, we find that innovation and technology are crucial for economic growth and carbon emission reduction (Ma and Zhu 2022; Guo et al. 2023). Given CTFP's nature, calculated based on economic growth and carbon emissions, we consider innovation and technology as potential mediator variables. Moreover, China's vast regions encompass diverse economic levels, populations, and natural resources. Different regions face unique challenges in reconciling the economy-environment conflict. Therefore, we propose the following hypotheses.

Hypothesis 2: DE indirectly affects CTFP through technology innovation.

Hypothesis 3: The impact of DE on CTFP is spatially heterogeneous and has spatial spillover effects.

Models established

Building upon our theoretical analysis and the proposed hypotheses, this section introduces three models in our study: the benchmark model, mechanism model, and spatial model.

Benchmark model

The least-square dummy variable (LSDV) method can estimate the effects of variables that remain constant over time. The fundamental concept of LSDV is to treat the unobservable

individual effects γ_i as parameters to be estimated so that the regression slopes of i cross sections are guaranteed to be the same, and the intercepts are different. This method enables the estimation of the heterogeneity of each person as well as the impact of constant variables, as shown in Eq. (1):

$$CTFP_{it} = \gamma_i + \alpha_1 DE_{it} + \alpha_2 DE_{it}^2 + \beta control_{it} + \mu_i + \theta_t + \varepsilon_{it}, \tag{1}$$

where $CTFP$ denotes the low-carbon green total factor productivity of province i in year t ; DE and $control$ denote the digital economy and control variables, respectively. μ_i indicates the province fixed effect, θ_t represents the year fixed effect, and ε_{it} is the random disturbance term. To ensure data stationarity, all variables are logarithmic in the model.

In line with the effect mechanism test model introduced by Baron and Kenny(1986), this study adopts the classical three-step approach to assess the impact path of DE on CTFP, and the steps are illustrated in Eq. (2) and Eq. (3):

$$MID_{it} = \gamma_i + \alpha_1 DE_{it} + \alpha_2 DE_{it}^2 + \beta control_{it} + \mu_i + \theta_t + \varepsilon_{it}, \tag{2}$$

$$CTFP_{it} = \gamma_i + \alpha_1 DE_{it} + \alpha_2 DE_{it}^2 + \alpha_3 MID_{it} + \beta control_{it} + \mu_i + \theta_t + \varepsilon_{it}, \tag{3}$$

MID denotes the mechanism variable; the other variables are set as before. First, Eq. (2) tests whether the effect of the DE on MID is significant, and if the coefficients of DE variables are significant, Eq. (3) can be conducted.

Spatial econometric model

Moran's index

Moran's index is used to determine whether the variables are spatially correlated, which is written as in Eq. (4). For calculating Moran's index, the following steps are in Eq. (5) and Eq. (6):

$$MorantSI = \frac{n}{S_0} \times \frac{\sum_{i=1}^n \sum_{j=1}^n w_{ij} (y_i - \bar{y})(y_j - \bar{y})}{\sum_{i=1}^n (y_i - \bar{y})^2}, \tag{4}$$

$$S_0 = \sum_{i=1}^n \sum_{j=1}^n w_{ij}, \tag{5}$$

$$\bar{y} = \frac{\sum_{i=1}^n y_i}{n}, \tag{6}$$

where n denotes the province's number, and y represents the values of each province. The further $Moran's I$ is away from zero, the stronger the spatial correlation is.

Spatial durbin model

In this study, we acknowledge the presence of spatial heterogeneity and correlation in CTFP among different regions. To analyze the variations and correlations between regions, we utilize a spatial model to empirically test the effects of DE on regional CTFP. There are several spatial models available, including the spatial autoregressive model (SAR), spatial Durbin model (SDM), and spatial error model (SEM). However, SAR and SEM models do not consider spatial autocorrelation and spatial spillover effects. In contrast, the SDM model incorporates the spatial correlation of the dependent variable and the spatial spillover effects of the independent variables. In this study, we utilize the SDM model and evaluate its suitability using the Hausman, Wald, and LR tests. The results of these tests are shown in Table 1. The Hausman test indicates that the fixed-effects model is more suitable for the data at hand. Furthermore, the Wald and LR tests indicate that the SDM cannot be simplified to the SAR or SEM models. Hence, we select the fixed-effect SDM model, represented by Eq. (7), to examine the spatial spillover effect of DE on CTFP:

$$CTFP_{it} = \rho \sum_{j=1}^n w_{ij}CTFP_{jt} + \alpha_1 DE_{it} + \alpha_2 DE_{it}^2 + \beta_1 control_{it} + \delta_1 \sum_{j=1}^n w_{ij}DE_{jt} + \delta_2 \sum_{j=1}^n w_{ij}DE_{jt}^2 + \delta_3 \sum_{j=1}^n w_{ij}control_{jt} + \mu_i + \theta_t + \varepsilon_{it}, \tag{7}$$

Geographical proximity matrix

Before estimating the model parameters, we set the spatial weight matrix. This study establishes the spatial adjacency matrix in the form of Eq. (8):

$$w_{ij} = \begin{cases} 1, & \text{province } i \text{ and province } j \text{ not border, or } i = j; \\ 0, & \text{province } i \text{ and province } j \text{ border;} \end{cases} \tag{8}$$

Variable selection

This study uses provinces as the observation unit. We selected 30 provinces in China for the survey (except Tibet, Hong Kong, Macau, and Taiwan), including

municipalities: Beijing (BJ), Tianjin (TJ), Shanghai (SH), Chongqing (CQ), and provinces: Hebei (HE), Shanxi (SX), Liaoning (LN), Jilin (JL), Heilongjiang (HL), Jiangsu (JS), Zhejiang (ZJ), Anhui (AH), Fujian (FJ), Jiangxi (JX), Shandong (SD), Henan (HA), Hubei (HB), Hunan (HN), Guangdong (GD), Hainan (HI), Sichuan (SC), Guizhou (GZ), Yunnan (YN), Shaanxi (SN), Gansu (GS), Qinghai (QH), Inner Mongolia (NM), Guangxi (GX), Ningxia (NX), Xinjiang (XJ).

Explained variable

Calculation method of CTFP

The Data Envelopment Approach (DEA) method can characterize CTFP well. It can measure the relationship between capital, human and energy input, economic output, and carbon emissions output (Tone and Tsutsui 2010). The super slack-based measure (SSBM) of the DEA method can estimate the efficiency under unexpected output and addresses

the issue of input–output relaxation (Tang et al. 2023).

$$\min \frac{1 - \frac{1}{m} \sum_{i=1}^m \frac{s_i^-}{x_i}}{\varphi + \frac{1}{s+q} (\sum_{r=1}^s \frac{s_r^+}{y_r} + \sum_{q=1}^p \frac{s_q^-}{b_q})} \tag{9}$$

$$s.t. \begin{cases} X\lambda + s_i^- = x_i; \\ Y\lambda - s_r^+ = y_r; \\ b\lambda + s_q^- = b_q; \\ \lambda \geq 0, s_i^-, s_r^+, s_q^- \geq 0, \end{cases} \tag{10}$$

where X denotes inputs, Y indicates expected outputs, and b represents unexpected outputs, s_i^- , s_r^+ , and s_q^- denote the slack in X , Y , and b , respectively.

Input and output

Drawing from the literature (Li and Lin 2016; Li and Wu 2017; Lee and Lee 2022), we adopt specific input and output variables for our analysis. The selected variables are as follows: capital, labor, and energy as inputs for CTFP, real GDP as the expected output, and carbon emissions as the unexpected output. Capital input is measured by the capital stock, labor input by the total employment, and energy input by electricity consumption. The descriptive statistics of these variables are shown in Table 2.

Table 1 Results of Hausman, Wald, and LR test

	chi-value	p-value
Hausman test	181.73***	0.0000
Wald Test for SAR	18.76***	0.0090
Wald Test for SEM	19.52***	0.0067
LR Test for SAR	21.62*	0.0057
LR Test for SEM	23.15**	0.0032

The symbols *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively

For capital stock measurement, we use the perpetual inventory method to calculate, as shown in the following Eq. (11):

$$K_{it} = K_{it-1}(1 - \delta_{it}) + I_{it}, \tag{11}$$

K refers to the capital stock, and I is the total social fixed asset investment. δ refers to the fixed asset depreciation rate. This paper used 2000 as the base period, where the fixed asset investment price index deflates the total fixed asset investment.

Results of CTFP measurement

The measurement results of CTFP in 30 provinces are visually presented in Figs. 3, 4, and 5, depicting the changing trend across different geographic areas from 2011 to 2020. For ease of representation, the provinces have been classified

into three regions (eastern, central, and western) according to their geographical locations.

From the temporal trends, it is evident that CTFP has not significantly improved over the past decade. Provinces with initially higher CTFP did not sustain their superior performance nationwide, while provinces with lower CTFP experienced a decline. These findings highlight the need for effective strategies to enhance CTFP and ensure sustained progress across all provinces. Furthermore, the simultaneous occurrence of substantial carbon emissions alongside rapid economic growth emphasizes the persistent environmental pollution resulting from the current economic development model. This underscores the urgent need to address the issue of CO2 emissions and find sustainable solutions.

Figure 6 reflects the spatial distribution of CTFP in 2011 and 2020. Geographically, the regions with higher CTFP are predominantly concentrated in the eastern region, particularly in the eastern coastal areas such as SH, known

Table 2 Input and output of CTFP

	Variables	Obs	Mean	SD	Min	Max	Units
Input	Labor	300	85,188.5	62,970.4	6374.0	321,658.7	ten thousand
	Capital	300	2588.3	1639.0	239.3	7039.0	billion
	Energy	300	1999.9	1435.1	185.3	6940.0	billion KWH
Output	Expected: GDP	300	16,695.9	12,555.2	1524.8	57,183.0	billion
	Unexpected: CO ₂ emission	300	331,879.9	212,933.0	34,900.0	972,587.0	kiloton

Fig. 3 Changes of CTFP in eastern region

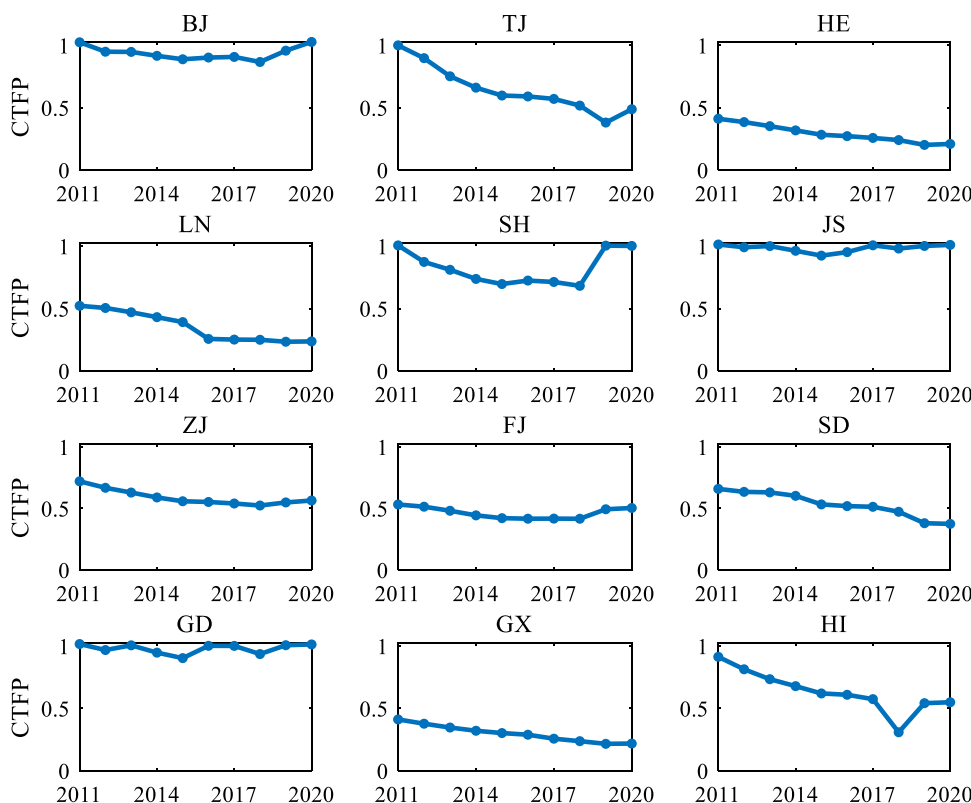


Fig. 4 Changes of CTFP in central region

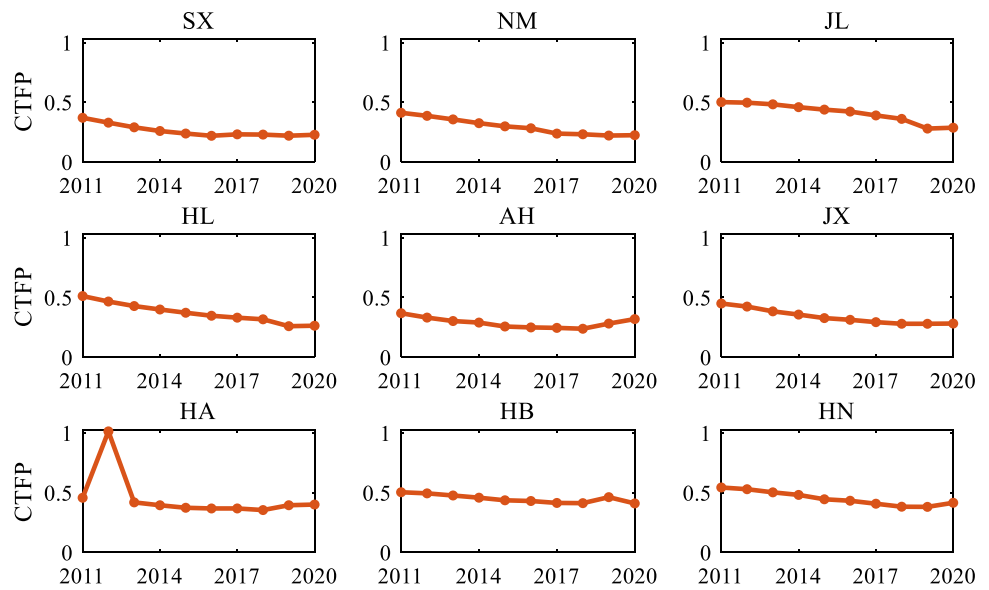
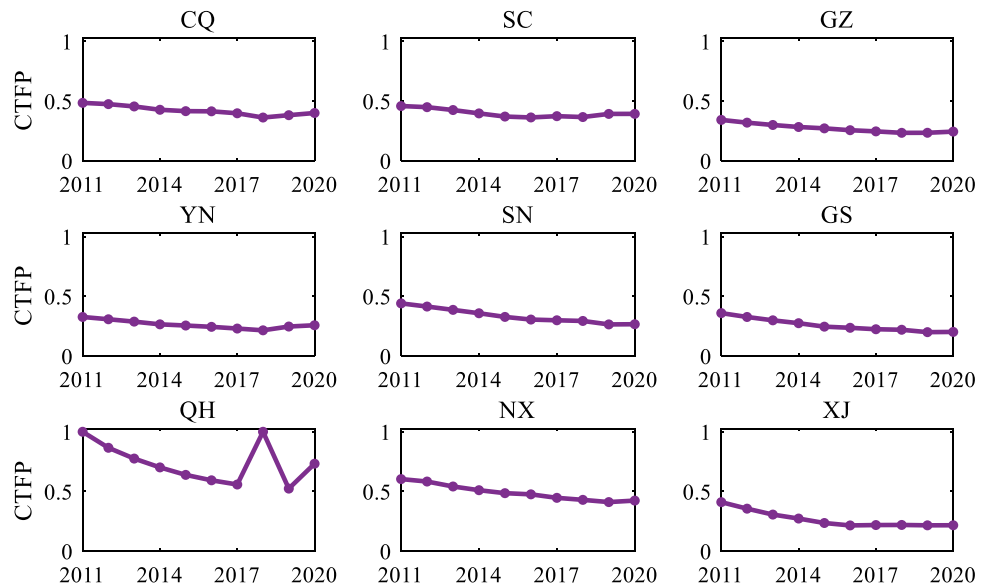


Fig. 5 Changes of CTFP in western region



for their advanced economic development. In contrast, the western region exhibits significant differentiation in CTFP, with many provinces experiencing lower levels of CTFP, including XJ, GS, and YN. However, QH and NX belong to provinces with higher CTFP, and the CTFP of these two provinces is comparable to that of the better-developed eastern coastal region. Overall, there is a general pattern of decreasing CTFP from the eastern region toward the western region.

Mechanism variables

Oh(2010) proposed the Global Malmquist-Luenberger index (GML), which is based on the directional distance function

(DDF) of the SBM. This index can provide feasible solutions for linear programming. The method measures CTFP with dynamic characteristics by introducing changes in production efficiency at periods t and $t + 1$. Meanwhile, the GML index can be divided into two components: technical efficiency and technical progress. This paper uses technology efficiency (EC) and technology progress (TC) when measuring technology innovation's technical efficiency and progress, respectively. The specific calculation formulae are shown in Eq. (12) to Eq. (14):

$$\begin{aligned}
 GML_0^{t+1}(x^{t+1}, y^{t+1}, x^t, y^t) &= \left[\frac{D_0^t(x^{t+1}, y^{t+1})D_0^{t+1}(x^{t+1}, y^{t+1})}{D_0^t(x^t, y^t)D_0^{t+1}(x^t, y^t)} \right]^{\frac{1}{2}} \\
 &= EC_0^{t+1} \times TC_0^{t+1},
 \end{aligned}
 \tag{12}$$

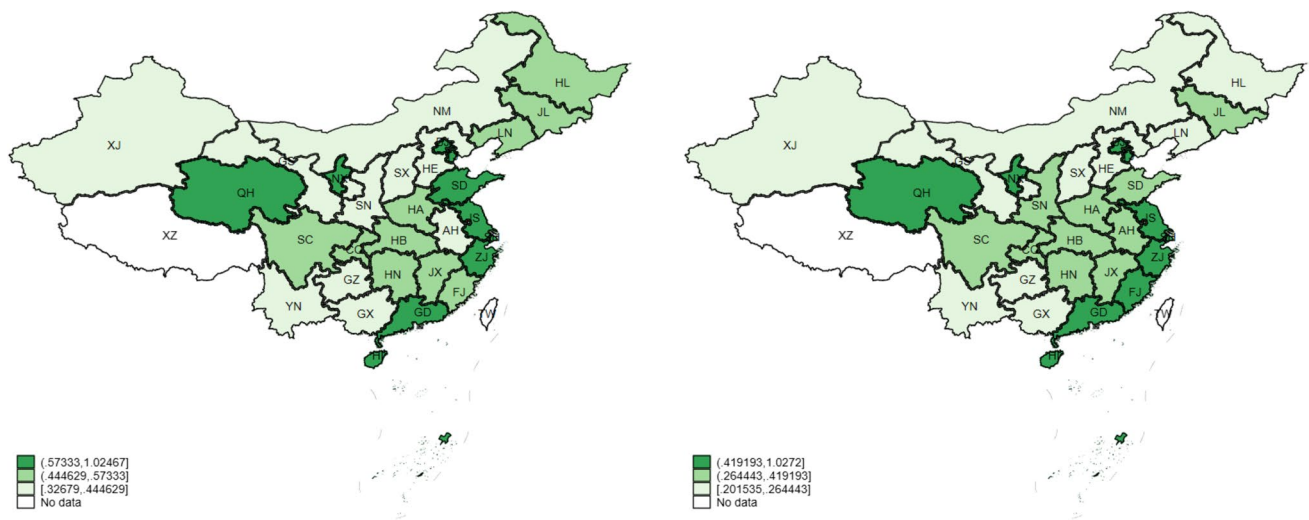


Fig. 6 Spatial distribution of CTFP in 2011 and 2020

$$EC_0^{t+1} = \frac{D_0^{t+1}(x^{t+1}, y^{t+1})}{D_0^t(x^t, y^t)}, \tag{13}$$

$$TC_0^{t+1} = \left(\frac{D_0^t(x^{t+1}, y^{t+1})D_0^t(x^t, y^t)}{D_0^{t+1}(x^{t+1}, y^{t+1})D_0^{t+1}(x^t, y^t)} \right)^{\frac{1}{2}}, \tag{14}$$

where D represents the directional distance function (DDF), x and y denote the innovation input and output vectors, respectively, and t denotes the year. Innovation labor input, innovation capital input, and expected output are measured by R&D researcher number, R&D capital stock, and patents granted number, respectively. R&D capital stock is calculated by the perpetual inventory method. GML reflects the growth of CTFP from t to $t + 1$, that is, each year's growth rate compared to the previous year. So, the first year's value is 1 in this paper, and each year's value is the previous year's

value multiplied by the growth rate. Innovation data are from the China Science and Technology Statistical Yearbook.

Explanatory variables

DE index system

Previous studies (Wu et al. 2021; Wang et al. 2022b; Du and Ren 2023) have commonly measured the DE using infrastructure construction, industrialization, and digital finance. Building upon this existing research, we establish a comprehensive evaluation framework for DE, as shown in Table 3.

Infrastructure data is obtained from the National Research Network database, industrial development data is obtained from the CSMAR database, and digital financial inclusion development index is obtained from Digital Finance Research Center of Peking University.

Table 3 DE index system

	Index explanatory	Units
Infrastructure	Length of fiber optic cable line	kilometers
	Length of long-distance fiber optic cable line	ten thousand kilometers
	Internet broadband access port	ten thousand
	Mobile phone exchange capacity	ten thousand households
Industrial development	Industrial enterprise technology introduction expenses	ten thousand
	Industrial enterprise technology transformation expenses	ten thousand
	Software industry business revenue	hundred million
	Number of software industry employees	person
	Number of software companies	company
Digital finance	Digital financial inclusion development index	

DE calculation

In determining the index system, various methods such as hierarchical analysis, entropy weight method, and principal component analysis (PCA) are commonly employed. PCA is particularly useful for analyzing the correlation between different data and condensing the information provided by these data. Given the specific correlation and homogeneity present in the DE data, we adopt PCA as the method of choice to measure DE. By utilizing PCA, we can effectively retain and condense the primary information of the data.

To calculate the indices for infrastructure, industrial development, and digital finance, this paper employs the global principal component analysis (GPCA) method. Unlike classical PCA, which is suitable for cross-sectional data only, GPCA integrates PCA with time series analysis, allowing for the exploration of a system's overall trajectory over time (Zhou et al. 2020). The development indices for infrastructure, industrial development, and digital finance are calculated separately. Subsequently, the DE development index is derived based on these individual indices. We need to calculate the eigenvalues and eigenvectors of each principal component by using principal component analysis (Pan et al. 2022). Then, we calculate the DE index in Eq. (15):

$$F = \frac{\lambda_1}{\sum_{j=1}^m \lambda_j} F_1 + \frac{\lambda_2}{\sum_{j=1}^m \lambda_j} F_2 + \dots + \frac{\lambda_m}{\sum_{j=1}^m \lambda_j} F_m, \quad (15)$$

where λ_j and F denote the eigenvalues and eigenvectors of the infrastructure covariance matrices, industrial development covariance matrices, and digital finance covariance matrices, respectively.

DE measurement results

Figures 7, 8, and 9 present the measurement results of DE in 30 provinces from 2011 to 2020. Over the past decade, there has been a rapid increase in DE across all provinces in China, driven by the Internet's rapid development and continuous technological progress. In fact, DE has shown a doubling of growth during this period. However, there still be a more significant gap in the development of DE among provinces. Provinces such as GD, SN, JS, and SH have exhibited notable development advantages in DE, while some central and western provinces still require additional development momentum.

The spatial development of DE in 2011 and 2020 is reflected in Fig. 10. It reveals that the regions with significant DE development extend beyond the eastern region, covering other parts of the country as well. In particular, with its abundant local resources and geographical diversity,

Fig. 7 Changes of DE in eastern region

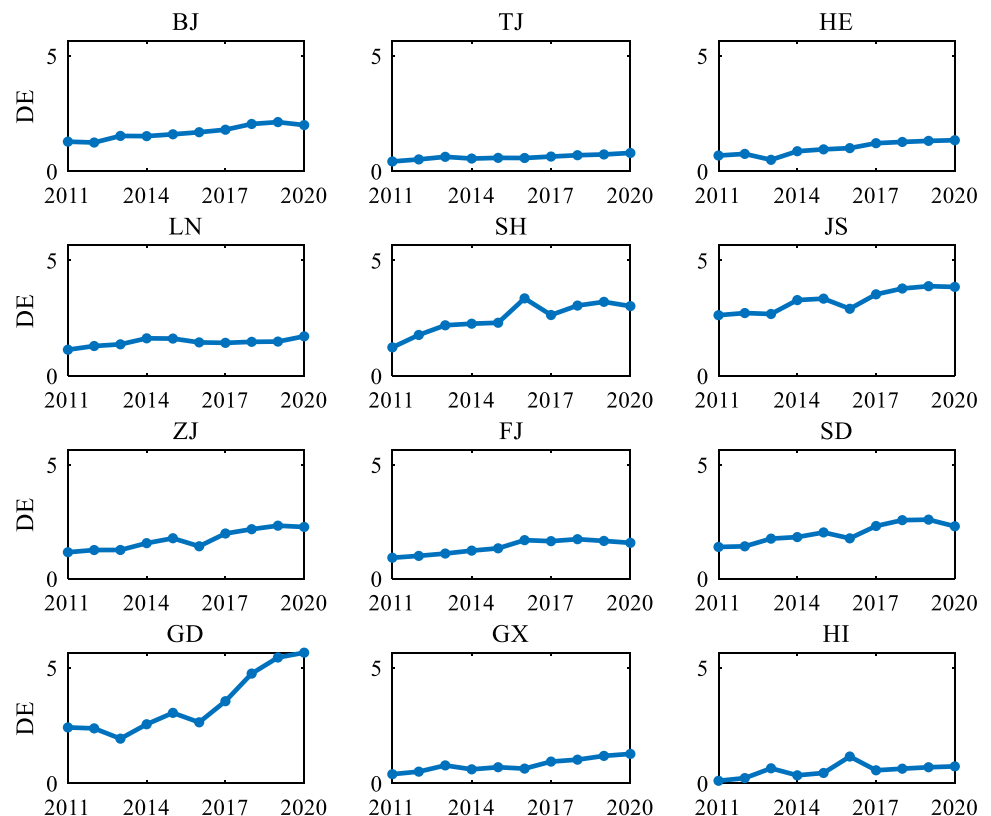


Fig. 8 Changes of DE in central region

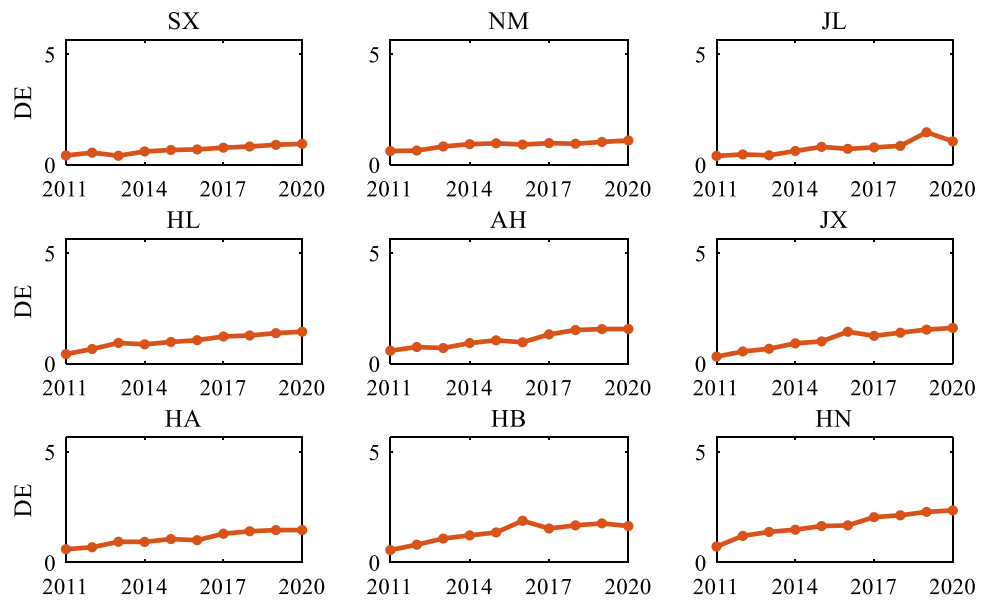
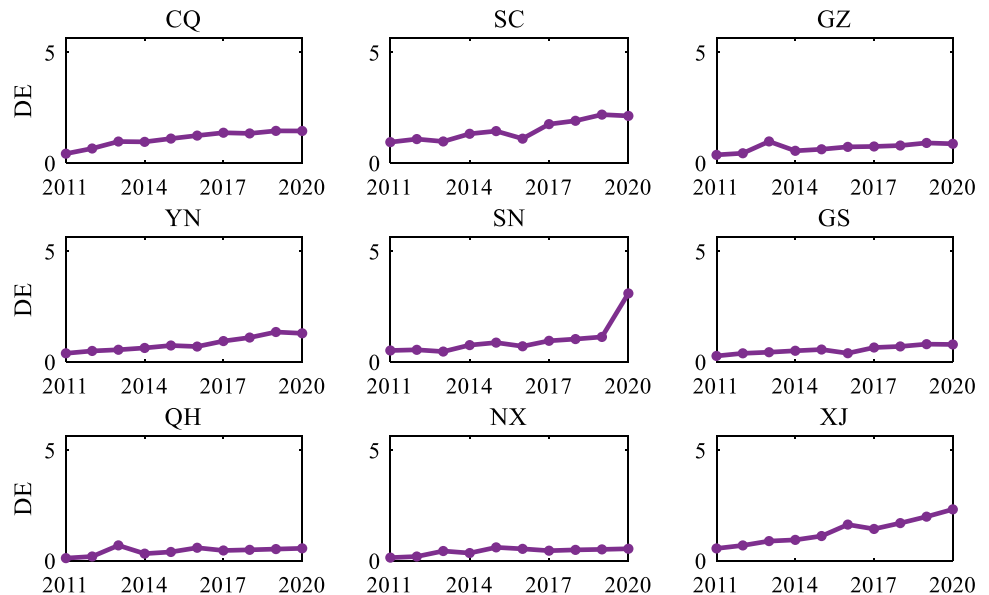


Fig. 9 Changes of DE in western region



the western region has emerged as a hub for digital solid economy provinces like SN and XJ. However, the western region also encompasses provinces with relatively poor DE development, such as QH, GS, and NX, also located in the western region. Over time, the DE development gap among provinces in the western region has been widening, highlighting the need for more balanced development efforts.

The central regions have shown limited progress in the development level of DE, with only HN exhibiting a relatively better level of development. The remaining central provinces require additional economic development momentum to catch up. However, it is worth noting that there has

been a trend towards a more balanced geographical distribution of DE across the country.

Generally, provinces with higher DE levels are predominantly located in the eastern region, particularly along the eastern coastal areas. The central region has been experiencing slower development and requires more significant momentum for improvement. Despite its initial disadvantages, the western region has shown rapid development in DE, although there is still much room for improvement. Over the period from 2011 to 2020, the DE development gap between provinces has gradually diminished. However, a notable development gap still needs to be addressed.

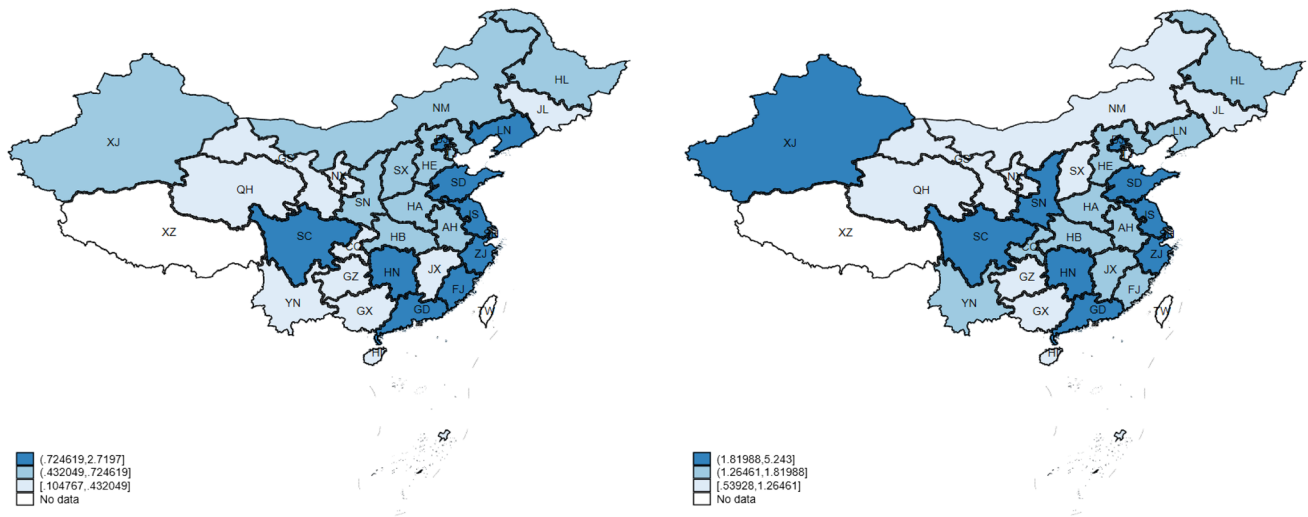


Fig. 10 Spatial distribution of DE in 2011 and 2020

Control variables

To mitigate the potential influence of omitted variables in our empirical analysis, we incorporate several control variables based on relevant literature (Dong et al. 2022). These control variables are chosen based on their known effects on economic growth or carbon emissions. The selected control variables are as follows. (1) Urbanization: urban population/total population. This variable represents the urban population as a proportion of the total population. Urbanization has been found to have a negative effect on carbon emissions (Sun and Dong 2022). (2) Economic development: GDP per capita is measured. Higher levels of economic development are often associated with increased carbon emissions due to increased economic and industrial activities (Cheng et al. 2023). (3) Foreign opening: This variable captures the extent of goods import and export relative to GDP. The expansion of foreign trade can bring an increase in carbon emissions (Zhang et al. 2021). (4) Financial development: The RMB loan balance is used as a proxy for financial development.

The growth of the financial sector is often accompanied by carbon emissions (Wang et al. 2020). (5) Government support: government expenditure is included as a measurement. Government support plays a vital role in carbon reduction efforts (Yao et al. 2020). (6) Industrial structure: The proportion of secondary industry GDP to tertiary industry GDP. The composition of industries in an economy is closely related to economic performance (Du and Ren 2023). It is vital to note that the units of economic development, financial development, and government support vary (e.g., ten thousand, hundred million, and ten billion, respectively) depending on the specific measurement used in the dataset.

Descriptive statistics

Table 4 provides statistical descriptions of the variables used in the analysis. All variables are presented in logarithmic form and exhibit favorable data stability with no significant outliers. The CTFP and control variables data are sourced from China/Provincial Statistical Yearbooks and Wind data

Table 4 Descriptive statistics

Variable	Definition	Obs	Mean	S.D	Min	Max
<i>CTFP</i>	Low-carbon green total factor productivity	300	1.6316	0.1977	1.3001	2.0117
<i>EC</i>	Technological innovation efficiency	300	2.0004	0.0907	1.4936	2.7258
<i>TC</i>	Technological innovation progress	300	2.0300	0.1002	1.4264	2.6102
<i>DE</i>	Digital economy	300	2.0135	0.2783	1.0202	2.7196
<i>URB</i>	Urbanization	300	1.7621	0.0870	1.5444	1.9523
<i>ECO</i>	Economic development	300	2.5329	0.1710	2.1756	2.9384
<i>FDI</i>	Foreign opening	300	2.1945	0.7498	-0.7817	3.2809
<i>FIN</i>	Financial development	300	2.5726	0.3528	1.6643	3.3638
<i>GOV</i>	Government support	300	3.6906	0.4348	2.5356	4.7945
<i>IND</i>	Industrial structure	300	2.0444	0.1817	1.7144	2.7240

base. The interpolation method was used to fill in the gaps left by missing data.

Results and discussion

Benchmark regression results

Table 5 presents the results obtained from the fixed-effects LSDV method. Models (1) to (5) represent the outcomes of fixed effects models. Specifically, model (1) corresponds to the results derived from Eq. (1), while models (2) and (3) reflect the estimation outcomes of Eq. (2) and Eq. (3), with EC serving as the mechanism variable. Similarly, models (4) and (5) illustrate the estimation results with TC as the mechanism variable.

The estimation results from the model (1) reveal a significant U-shaped relationship between *DE* and *CTFP*, indicating that the effect of *DE* on *CTFP* is initially negative and then becomes positive. Initially, as *DE* requires substantial infrastructure construction, it leads to increased carbon emissions and hampers the improvement of *CTFP*. However, when *DE* reaches an inflection points at 2.16, it starts to promote the development of *CTFP*.

Additionally, the control variables *URB* and *FIN* exhibit a significantly negative impact on *CTFP*, suggesting that

urbanization contributes to increased carbon emissions and further development of green finance is needed. In contrast, *ECO* exhibits a notable positive impact on *CTFP*, indicating a balance between economic growth and carbon emissions reduction. Moreover, the government's support (*GOV*) plays a vital role in carbon reduction as it significantly promotes *CTFP*.

The visual relationship between *CTFP* and *DE* in the model (1) is visualized in Fig. 11. The coordinates of *CTFP* and *DE* in 2020 are represented by the abbreviated letters

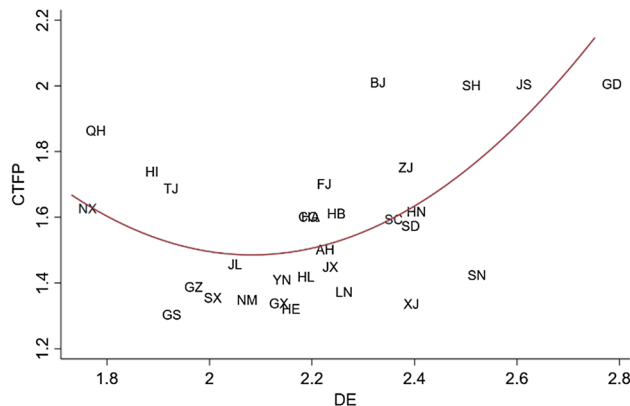


Fig. 11 The fitting curve of *CTFP* and *DE*

Table 5 Results of benchmark regression

	<i>CTFP</i> Model (1)	<i>EC</i> Model (2)	<i>CTFP</i> Model (3)	<i>TC</i> Model (4)	<i>CTFP</i> Model (5)
<i>EC</i>			0.018 (-0.64)		
<i>TC</i>					0.067** (2.55)
<i>DE</i>	-0.273** (-2.51)	-1.048*** (-4.21)	-0.291*** (-2.59)	0.940*** (3.70)	-0.336*** (-3.05)
<i>DE</i> ²	0.063** (2.09)	0.281*** (4.07)	0.068** (2.81)	-0.234*** (-3.33)	0.078** (2.59)
<i>URB</i>	-1.032*** (-5.33)	0.458* (-1.03)	-1.040*** (-5.36)	-0.691 (-1.53)	-0.986*** (-5.12)
<i>ECO</i>	0.913*** (11.23)	-0.172 (-0.92)	0.910*** (11.16)	0.108 (0.57)	0.905*** (11.25)
<i>FDI</i>	-0.023 (-1.61)	0.022 (0.68)	-0.023 (-1.58)	-0.034 (-1.04)	-0.021 (-1.46)
<i>FIN</i>	-0.330** (-2.49)	-0.155 (-0.51)	-0.333** (-2.50)	0.360 (1.16)	-0.354*** (-2.69)
<i>GOV</i>	0.096*** (2.92)	0.332 (0.44)	0.096*** (2.93)	-0.002 (-0.03)	0.096*** (2.96)
<i>IND</i>	0.063 (1.06)	-0.109 (-0.80)	0.061 (1.02)	0.047 (0.34)	0.059 (1.01)
<i>Adj-R</i> ²	0.963	0.063	0.963	0.205	0.964

The symbols *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively

for each province. The figure illustrates that regions and cities located to the right of the inflection point experience continuous development of *DE* and *CTFP*, with *DE* promoting *CTFP* growth. For provinces situated to the left but near the inflection point, the promotion of *DE* inhibits the improvement of *CTFP*. In the early stages of *DE* development, intensive infrastructure construction and investments in resources, workforce, and finances result in carbon emissions, exerting a suppressive effect on *CTFP*. However, *DE* has reached a more mature stage for the provinces and cities near the inflection point, and further development significantly reduces carbon emissions. Provinces are located on the left side. distant from the inflection point, lag in economic growth, but possess abundant geographic resources and sparse populations. Despite their less developed *DE*, they exhibit lower carbon emissions, leading to higher *CTFP* values.

Models (2) and (3) reveal that *DE* has a significant U-shaped effect on *EC*. Once *DE* surpasses a threshold, it starts to promote *EC*. However, the effect of *EC* on *CTFP* is insignificant, suggesting that *EC* does not necessarily enhance input and output efficiency in industrial enterprises. This observation suggests that there is no strong correlation between *EC* and *CTFP*.

On the other hand, models (4) and (5) present the results of the mediating effect test of *TC*. *DE* influences *CTFP* through *TC*, and *TC* has a facilitating effect on *CTFP*. This implies that advancements in *TC* will improve resource utilization within enterprises. By employing new technologies and materials through *TC*, enterprises enhance production efficiency, thereby contributing to improved *CTFP*.

Robustness tests

The robustness of the benchmark model is tested in this article using two methods. First, the fixed effects model is replaced with a random effects model. The regression results in models (6) to (10) are presented in Table 6. It is observed that there is no significant variation in the signs of the explanatory variables, indicating consistent relationships.

Second, an instrumental variable (IV) approach is adored to address potential endogeneity issues caused by missing unobservable variables, reverse causality, or measurement errors in the indicator system (Wu et al. 2021). The spherical distance from each province to Zhejiang province, which serves as the core province of China's Internet, is used as the IV for *DE* (Zhang et al. 2019). The farther away from

Table 6 Results of robustness test

	Random effects test					IV test				
	<i>CTFP</i>	<i>EC</i>	<i>CTFP</i>	<i>TC</i>	<i>CTFP</i>	<i>CTFP</i>	<i>EC</i>	<i>CTFP</i>	<i>TC</i>	<i>CTFP</i>
	Model (6)	Model (7)	Model (8)	Model (9)	Model (10)	Model (11)	Model (12)	Model (13)	Model (14)	Model (15)
<i>EC</i>			0.014 (-0.50)					0.001 (0.02)		
<i>TC</i>					0.077*** (3.04)					0.047* (1.8)
<i>DE</i>	-0.266** (-2.28)	-1.043*** (-4.07)	-0.280** (-0.50)	0.944*** (3.80)	-0.336*** (-2.85)	0.209*** (3.66)	0.190 (1.42)	0.209*** (3.64)	-0.174 (-1.29)	0.217*** (3.81)
<i>DE</i> ²	0.062* (1.92)	0.278** (3.92)	0.066* (1.98)	-0.236*** (-3.43)	0.079** (2.44)	-0.105*** (-5.18)	-0.073 (-1.55)	-0.105*** (-5.14)	0.057 (1.19)	-0.108*** (-5.32)
<i>URB</i>	-1.068*** (-4.81)	0.442 (-0.95)	-1.074*** (-4.83)	-0.670 (-1.53)	-1.009*** (-4.52)	-1.168*** (-6.18)	-0.940** (-2.13)	-1.167*** (-6.11)	-0.241 (-0.54)	-1.157*** (-6.14)
<i>ECO</i>	0.926*** (10.49)	-0.156** (-0.81)	0.925*** (10.46)	0.110 (0.59)	0.920*** (10.48)	0.917*** (11.22)	-0.12 (-0.63)	0.917*** (11.19)	0.078 (0.40)	0.913*** (11.22)
<i>FDI</i>	-0.029** (-1.94)	0.025 (0.74)	-0.029* (-1.90)	-0.028 (-0.86)	-0.024 (-1.63)	-0.013 (-1.11)	0.053 (-1.61)	-0.016 (-1.11)	-0.061* (-1.83)	-0.013 (-0.91)
<i>FIN</i>	-0.302** (-2.04)	-0.153 (-0.48)	-0.304** (-2.05)	0.359 (1.19)	-0.328** (-2.21)	-0.335** (-2.52)	-0.0854 (-0.27)	-0.335** (-2.51)	0.337 (1.07)	-0.351*** (-2.64)
<i>GOV</i>	0.099*** (2.78)	0.020 (0.25)	0.099*** (2.77)	-0.013 (-0.18)	0.094*** (2.68)	0.092*** (2.79)	0.019 (-0.25)	0.092*** (2.79)	0.009 (0.12)	0.092*** (2.79)
<i>IND</i>	0.075 (1.17)	-0.116 (-0.82)	0.073 (1.18)	0.038 (0.28)	0.068 (1.07)	0.0463 (0.78)	-0.132 (-0.95)	0.0464 (0.78)	0.0857 (0.61)	0.0422 (0.72)
<i>WithinR</i> ²	0.802	0.165	0.802	0.316	0.807	0.962	0.009	0.962	0.166	0.962

The symbols *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively

Zhejiang Province, the lower the level of DE, so the IV variable has an inverse relationship with DE.

Model (11) to model (15) represent the estimation results using the instrumental variable, showing a significant inverted-U-shaped relationship between the IV and CTFP. This finding reinforces the robustness of the model and indicates that the instrumental variable helps address endogeneity concerns effectively.

Heterogeneity

In this study, the impact of DE on CTFP is examined with consideration of regional heterogeneity in economic growth across the 30 provinces of China. The provinces are divided into four regions based on government economic policy and regional geography: Eastern, Central, Western, and Northeast. Additionally, the provinces are classified into three groups based on their level of economic development: high GDP, middle GDP, and low GDP.

The regression results for each region are presented in Table 7, with models (16) to (19) representing the heterogeneity tests classified by policy and geography and models (20) to (22) representing the heterogeneity tests classified by GDP level. The fitted plots of the relationship between CTFP and DE in the different regions are illustrated in Fig. 12 and Fig. 13, with the coordinates representing the respective provinces. The findings reveal notable differences in the impact of DE across diverse regions of China.

In the eastern region, the impact exhibits a significant U-shaped relationship, with a larger coefficient for the quadratic term and an inflection point at 1.99, located to the left of the national inflection point. Moreover, most provinces in the eastern region are positioned to the right side of the inflection point. In the central region, the coefficient for the quadratic term is smaller than the national results, and the fitted plot indicates a positive trend. In the western region, the relationship also follows a U-shaped pattern, but around half of the regional provinces are still around the turning point. Conversely, the northeast region demonstrates a negative effect of DE on CTFP, indicating a weaker DE development in this region.

Regarding the classification based on GDP level, the high GDP region exhibits a significant U-shaped relationship, with an inflection point at 2.26 and all provinces located on the right side of the inflection point. Provinces in the middle GDP region and low GDP region are mostly positioned around the inflection point, with a steeper trend observed in the middle GDP region.

Spatial effect regression

Spatial correlation test

To conduct spatial regressions, it is essential to assess the spatial correlation of the core variables used in the study. Table 8 presents Moran's index of CTFP from 2011 to 2020. The results indicate that Moran's I statistics for CTFP are all greater than

Table 7 Results of heterogeneity test

	Classified by policy and geography				Classified by economic level		
	Eastern Model (16)	Central Model (17)	Western Model (18)	Northeast Model (19)	High GDP Model (20)	Middle GDP Model (21)	Low GDP Model (22)
<i>DE</i>	-0.601*** (-3.75)	-0.909 (-0.89)	-0.200 (-1.35)	-0.363 (-0.67)	-0.969*** (-3.42)	-0.170 (-0.79)	0.087 (0.41)
<i>DE</i> ²	0.151*** (3.29)	0.212 (0.79)	0.042 (1.01)	0.107 (0.76)	0.214*** (3.35)	0.043 (0.69)	-0.046 (-0.74)
<i>URB</i>	-1.070*** (-3.20)	-0.402 (-0.27)	0.865* (1.83)	1.263 (1.10)	-0.911*** (-3.54)	-0.081 (-0.08)	-0.214 (-0.44)
<i>ECO</i>	1.049*** (6.29)	1.300** (2.61)	0.449*** (3.29)	1.017*** (7.91)	1.110*** (9.85)	0.577** (2.46)	0.640*** (5.34)
<i>FDI</i>	0.040 (1.07)	0.021 (0.10)	-0.072*** (-4.38)	0.011 (0.57)	-0.022 (-0.83)	0.057 (1.29)	-0.039** (-2.31)
<i>FIN</i>	0.082 (0.33)	-1.134 (-1.56)	-0.846*** (-5.11)	0.159 (0.28)	0.227 (0.94)	-0.671** (-2.05)	-0.533*** (-2.73)
<i>GOV</i>	0.030 (0.47)	0.094 (0.90)	0.160*** (3.20)	0.062 (0.93)	-0.018 (-0.34)	0.120* (1.75)	0.062 (0.85)
<i>IND</i>	-0.036 (-0.20)	-0.058 (-0.25)	0.084 (1.13)	-0.040 (-0.46)	0.024 (0.19)	0.235 (1.32)	0.033 (0.45)
<i>Adj-R</i> ²	0.958	0.855	0.969	0.990	0.971	0.883	0.962

The symbols *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively

Fig. 12 The fitting curve of CTFP and DE in central region, eastern region, and western region

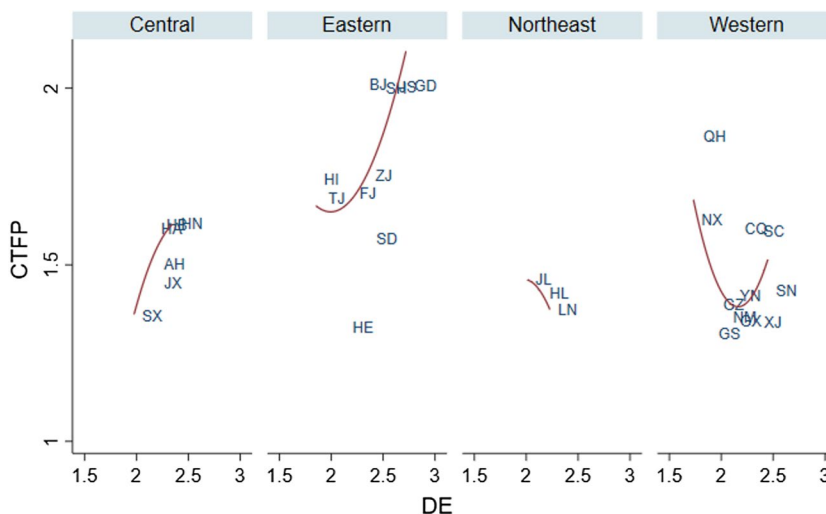


Fig. 13 The fitting curve of CTFP and DE in regions with different levels of economic development

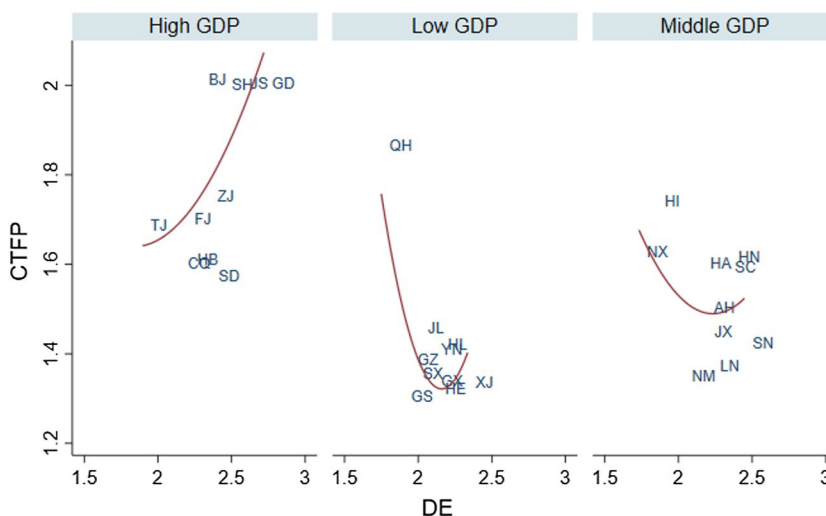


Table 8 Results of spatial autocorrelation test

Year	Moran's I	z
2011	0.303***	2.709
2012	0.174*	1.667
2013	0.251**	2.300
2014	0.240**	2.214
2015	0.217**	2.031
2016	0.247**	2.273
2017	0.262**	2.404
2018	0.070	0.851
2019	0.299***	2.705
2020	0.278**	2.529

The symbols *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively

zero and significant at the 5% level for most years. This suggests a significant spatial aggregation effect of the CTFP variable, and the spatial aggregation effect appears to be increasing. The

significant spatial autocorrelation observed in the CTFP supports the suitability of spatial econometric analysis.

Spatial effect results

In the spatial regression analysis conducted in this study, both the national and regional spatial effects were examined about the impact of DE on CTFP. The results, presented in Table 9, reveal that the U-shaped relationship between DE and CTFP, as observed in “Benchmark regression results” section, persists. The spatial regression results indicate that the effect is significant nationally and in the eastern region. However, the results vary when considering spatial spillover effects in neighboring regions.

In neighboring regions, the spatial spillover effect of DE on CTFP appears to have a negative impact or follows an inverted U-shaped pattern. In the central region, the lack of a significant impact of DE on CTFP can be attributed

Table 9 Results of spatial test

	Nationwide		Eastern		Central		Western		Northeast	
	Main	Wx	Main	Wx	Main	Wx	Main	Wx	Main	Wx
<i>DE</i>	-0.213** (-2.03)	0.320 (1.44)	-0.306* (-1.95)	0.518** (2.20)	-1.293 (-1.13)	-0.990 (-0.41)	-0.144 (-0.99)	-0.144 (-0.24)	0.730* (1.95)	1.586*** (3.37)
<i>DE</i> ²	0.045 (1.55)	-0.098* (-1.68)	0.0874* (1.85)	-0.120* (-1.85)	0.272 (0.91)	0.231 (0.37)	0.0255 (0.64)	0.0255 (0.15)	-0.212** (-2.01)	-0.452*** (-3.47)
<i>URB</i>	-1.22*** (-5.17)	-0.067 (-0.14)	-0.667*** (-2.60)	-0.534 (-0.81)	0.423 (0.16)	0.735 (0.14)	0.164 (0.30)	0.164 (-0.48)	1.805*** (4.14)	-0.281 (-0.21)
<i>ECO</i>	1.003*** (12.19)	0.105 (0.60)	1.546*** (10.65)	1.296*** (4.80)	1.649*** (3.37)	0.835 (0.62)	0.707*** (4.75)	0.707*** (-0.28)	1.018*** (13.63)	0.104 (0.49)
<i>FDI</i>	-0.019 (-1.38)	-0.001 (-0.05)	0.124*** (3.65)	0.208*** (3.31)	-0.115 (-0.57)	-0.161 (-0.38)	-0.087*** (-5.88)	-0.0871*** (-0.50)	0.00867 (0.76)	0.0286 (1.61)
<i>FIN</i>	-0.250* (-1.84)	0.281 (1.12)	-0.0509 (-0.23)	0.234 (0.65)	-0.387 (-0.44)	1.784 (1.05)	-0.886*** (-5.56)	-0.886*** (-2.26)	-6.230*** (-6.13)	-7.146*** (-6.49)
<i>GOV</i>	0.099*** (3.01)	-0.204*** (-2.89)	-0.128** (-1.98)	-0.237*** (-2.75)	-0.107 (-0.73)	-0.386 (-1.22)	3.23*** (3.23)	0.153*** (0.36)	0.258*** (5.30)	0.216*** (3.42)
<i>IND</i>	-0.048 (0.91)	-0.082 (-0.74)	-0.0306 (-0.22)	0.624** (2.52)	-0.268 (-1.02)	-1.024 (-1.25)	0.138** (2.18)	0.138** (-2.50)	0.379*** (4.13)	0.380*** (3.71)
<i>withinR</i> ²	0.773		0.433		0.693		0.843		0.788	

The symbols *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively

to the loss of talent and limited local resources, which may hamper the potential benefits of DE. Similarly, in the western region, the distance between provinces and abundant natural resources could contribute to the lack of significant impact on neighboring regions. Lastly, the northeast region shows a negative effect on both the local area and neighboring regions, indicating a poor development of DE.

Discussions

The analysis indicates a U-shaped relationship between DE and CTFP, with its influence primarily mediated through technological innovation progress. Furthermore, this impact demonstrates heterogeneity among various regions. Initially, it underscores the importance of the science and technology sector and underlines the necessity for addressing regional disparities. In this regard, the government assumes a central role in implementing regional policies.

The findings suggest that the eastern region, with its developed economy, robust social governance structure, and abundant talent and enterprises, can promote CTFP through DE. Provinces in the eastern region also exhibit a relatively easy ability to reach the inflection point, indicating a favorable balance between economic development and carbon emissions. However, the concentration of growth in the eastern region may lead to a siphoning effect, where resources, talents, and capital gravitate towards already developed provinces and cities such as BJ, SH, and GD. This phenomenon raises

concerns about the potential neglect of underdeveloped regions and the need to address resource grabbing.

In contrast, the central region faces challenges in its industrial development path, requiring more dynamic economic growth and a more comprehensive approach to DE. To enhance resource utilization efficiency and mitigate environmental pollution, the central region should focus on improving the application of digital technology in industrial production. The western region, mostly located around the inflection point in the empirical results, indicates the need for large-scale infrastructure construction, industrial upgrading, and talent attraction. Policies that support the development of clean and green industries, utilizing abundant wind and clean energy resources, can foster the growth of the western region while promoting sustainable development. The northeast region continues to experience decline, both within individual provinces and in relation to neighboring regions. The government has introduced revitalization plans to address the challenges faced by the northeast and rejuvenate its old industrial bases.

The high GDP region demonstrates a development advantage and a greater likelihood of achieving a balance between GDP growth and carbon emissions reduction. However, achieving this balance is relatively more challenging for underdeveloped regions. Therefore, the development plans for central China, the large-scale development of western China, and the revitalization of northeast China are crucial. Additionally, the government should formulate supportive

policies to assist underdeveloped regions and mitigate the potential siphoning effect, ensuring more equitable and sustainable development across different regions.

Conclusions and policy suggestions

Conclusions

In conclusion, this study investigates the relationship between DE and CTFP in China from 2011 to 2020, considering regional heterogeneity and the intermediary mechanism of technological innovation. The main findings suggest a U-shaped relationship between DE and CTFP, where DE initially inhibits CTFP but starts promoting it after reaching a turning point at 2.16. The eastern region and high GDP region exhibit a more significant impact of DE on CTFP, while other regions do not significantly increase in CTFP with DE.

The analysis of the intermediary mechanism reveals that technological development influences CTFP primarily through technological innovation progress, indicating the importance of technological advancements in improving CTFP.

Spatial effects indicate that DE in the eastern region affects its own CTFP and the CTFP of neighboring provinces. However, when DE reaches a certain level, it may have a suppressive effect on the CTFP of neighboring regions, possibly due to the "siphon effect" caused by the concentration of DE in more developed areas.

Overall, these findings contribute to our comprehension of the relationship between DE and CTFP in China and highlight the need for region-specific policies and measures to promote sustainable development and mitigate the potential negative effects of regional disparities.

Policy suggestions

Drawing upon the analysis and results, here are some policy recommendations to foster high-efficiency development and carbon emissions reduction in China.

Strengthen Carbon Emission Control and Environmental Protection: Given the declining trend in CTFP and the significant carbon emissions associated with economic development, the government should intensify efforts to monitor and control carbon emissions. This can be achieved through stricter regulations, promoting energy-efficient practices, and investing in environmental protection measures. Encouraging financial institutions and enterprises to invest in green projects will also be crucial. Additionally, increased support for environmental research and development can lead to innovative solutions for reducing carbon emissions.

Focus on Technology Innovation and Talent Development: As the analysis indicates that technology innovation progress plays a crucial role in enhancing CTFP, the government should prioritize policies and funding that support technology research and development. Providing incentives for high-emission industries to adopt digital technologies and innovative practices can enhance energy efficiency and mitigate carbon emissions.

Targeted Support for Provinces in Different Development Stages: Provinces that have surpassed the turning point and are on the right side of the inflection point should be supported in further developing their digital economy. Policies should focus on encouraging innovation, promoting technology transfer, and attracting investments to these regions. On the other hand, provinces that are still on the left side of the turning point, particularly those in the western and underdeveloped areas, should receive targeted support. Particular attention should be given to utilizing their abundant natural resources and clean energy to foster a green economy and industry.

Promote Interregional Collaboration and Information Sharing: The spatial analysis results reveal limited positive spillover effects between provinces and regional heterogeneity. To address this, the government should facilitate interregional collaboration and information sharing through digital technology. Encouraging the flow of talent and capital to less advanced regions and facilitating the exchange of digital technology expertise can foster mutual learning and development.

Authors' contributions Each named author has substantially contributed to conducting the underlying research and drafting this manuscript. Xiaoguang Zhou: Conceptualization, Supervision, Writing—review & editing. Jiayi Ji: Methodology, Data curation, Visualization, Writing—original draft.

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Data availability The datasets used and analyzed during the current study are available from the corresponding author upon reasonable request.

Declarations

Each of the authors confirms that this manuscript has not been previously published and is not currently under consideration by any other journal. Additionally, all authors have approved this paper's contents and agreed to publish it in Environmental Science and Pollution Research.

Ethics approval and consent to participate Not applicable.

Consent for publication All authors of the article consent to publish.

Competing interests The authors declare no competing interests.

References

- Baron RM, Kenny DA (1986) The moderator–mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *J Pers Soc Psychol* 51:1173
- Chen P (2022) Is the digital economy driving clean energy development? -New evidence from 276 cities in China. *J Clean Prod* 372:133783. <https://doi.org/10.1016/j.jclepro.2022.133783>
- Cheng Y, Zhang Y, Wang J, Jiang J (2023) The impact of the urban digital economy on China's carbon intensity: Spatial spillover and mediating effect. *Resour, Conserv Recycl* 189:106762. <https://doi.org/10.1016/j.resconrec.2022.106762>
- Deng H, Bai G, Shen Z, Xia L (2022) Digital economy and its spatial effect on green productivity gains in manufacturing: Evidence from China. *J Clean Prod* 378:134539. <https://doi.org/10.1016/j.jclepro.2022.134539>
- Dong F, Hu M, Gao Y, Liu Y, Zhu J, Pan Y (2022) How does digital economy affect carbon emissions? Evidence from global 60 countries. *Sci Total Environ* 852:158401. <https://doi.org/10.1016/j.scitotenv.2022.158401>
- Du M, Ren S (2023) Does the digital economy promote industrial green transformation? Evidence from spatial Durbin model. *J Inform Econ* 1:1–17. <https://doi.org/10.58567/jie01010001>
- Gao Y, Zhang M, Zheng J et al (2021) Accounting and determinants analysis of China's provincial total factor productivity considering carbon emissions. *China Econ Rev* 65:101576. <https://doi.org/10.1016/j.chieco.2020.101576>
- Godil DI, Yu Z, Sharif A, Usman R, Khan SAR (2021) Investigate the role of technology innovation and renewable energy in reducing transport sector CO2 emission in China: A path toward sustainable development. *Sustain Dev* 29:694–707. <https://doi.org/10.1002/sd.2167>
- Guo B, Wang Y, Zhang H, Liang C, Feng Y, Hu F (2023) Impact of the digital economy on high-quality urban economic development: Evidence from Chinese cities. *Econ Model* 120:106194. <https://doi.org/10.1016/j.econmod.2023.106194>
- Lee C, Lee C (2022) How does green finance affect green total factor productivity? Evidence from China. *Energy Econ* 107:105863. <https://doi.org/10.1016/j.eneco.2022.105863>
- Li K, Lin B (2016) Impact of energy conservation policies on the green productivity in China's manufacturing sector: Evidence from a three-stage DEA model. *Appl Energy* 168:351–363. <https://doi.org/10.1016/j.apenergy.2016.01.104>
- Li Z, Wang J (2022) The Dynamic Impact of Digital Economy on Carbon Emission Reduction: Evidence City-level Empirical Data in China. *J Clean Prod* 351:131570. <https://doi.org/10.1016/j.jclepro.2022.131570>
- Li B, Wu S (2017) Effects of local and civil environmental regulation on green total factor productivity in China: A spatial Durbin econometric analysis. *J Clean Prod* 153:342–353. <https://doi.org/10.1016/j.jclepro.2016.10.042>
- Li K, Kim DJ, Lang KR, Kauffman RJ, Naldi M (2020) How should we understand the digital economy in Asia? Critical assessment and research agenda. *Electron Commer Res Appl* 44:101004. <https://doi.org/10.1016/j.elerap.2020.101004>
- Liang L, Li Y (2023) How does government support promote digital economy development in China? The mediating role of regional innovation ecosystem resilience. *Technol Forecast Soc Chang* 188:122328. <https://doi.org/10.1016/j.techfore.2023.122328>
- Lin B, Huang C (2023) How will promoting the digital economy affect electricity intensity? *Energy Policy* 173:113341. <https://doi.org/10.1016/j.enpol.2022.113341>
- Luo K, Liu Y, Chen P, Zeng M (2022) Assessing the impact of digital economy on green development efficiency in the Yangtze River Economic Belt. *Energy Econ* 112:106127. <https://doi.org/10.1016/j.eneco.2022.106127>
- Lyu Y, Wang W, Wu Y, Zhang J (2023) How does digital economy affect green total factor productivity? Evidence from China. *Sci Total Environ* 857:159428. <https://doi.org/10.1016/j.scitotenv.2022.159428>
- Ma D, Zhu Q (2022) Innovation in emerging economies: Research on the digital economy driving high-quality green development. *J Bus Res* 145:801–813. <https://doi.org/10.1016/j.jbusres.2022.03.041>
- Mankiw NG, Romer D, Weil DN (1992) A contribution to the empirics of economic growth. *Q J Econ* 107:407–437
- Mohsin M, Phoumin H, Youn IJ, Taghizadeh-Hesary F (2021) Enhancing Energy and Environmental Efficiency in the Power Sectors: A Case Study of Singapore and China. *J Environ Assess Policy Manag* 23. <https://doi.org/10.1142/S146433322500181>
- Oh D (2010) A global Malmquist-Luenberger productivity index. *J Product Anal* 34:183–197
- Pan W, Xie T, Wang Z, Ma L (2022) Digital economy: An innovation driver for total factor productivity. *J Bus Res* 139:303–311. <https://doi.org/10.1016/j.jbusres.2021.09.061>
- Ren S, Hao Y, Xu L, Wu H, Ba N (2021) Digitalization and energy: How does internet development affect China's energy consumption? *Energy Econ* 98:105220. <https://doi.org/10.1016/j.eneco.2021.105220>
- Romer PM (1986) Increasing returns and long-run growth. *J Polit Econ* 94:1002–1037
- Sun J, Dong F (2022) Decomposition of carbon emission reduction efficiency and potential for clean energy power: Evidence from 58 countries. *J Clean Prod* 363:132312. <https://doi.org/10.1016/j.jclepro.2022.132312>
- Tang X, Zhou X, Kholaiif MMNH (2023) Does green finance achieve its goal of promoting coordinated development of economy–environment? Using the pollutant emission efficiency as a proxy. *Environ, Dev Sustain*. <https://doi.org/10.1007/s10668-023-03129-9>
- Tone K, Tsutsui M (2010) Dynamic DEA: A slacks-based measure approach. *Omega* 38:145–156
- Tong D, Zhang Q, Liu F et al (2018) Current Emissions and Future Mitigation Pathways of Coal-Fired Power Plants in China from 2010 to 2030. *Environ Sci Technol* 52:12905–12914. <https://doi.org/10.1021/acs.est.8b02919>
- Valadkhani A, Smyth R, Nguyen J (2019) Effects of primary energy consumption on CO2 emissions under optimal thresholds: Evidence from sixty countries over the last half century. *Energy Econ* 80:680–690. <https://doi.org/10.1016/j.eneco.2019.02.010>
- Wang L, Shao J (2023) Digital economy, entrepreneurship and energy efficiency. *Energy (oxf)*. <https://doi.org/10.1016/j.energy.2023.126801>
- Wang L, Wu H, Hao Y (2020) How does China's land finance affect its carbon emissions? *Struct Chang Econ Dyn* 54:267–281. <https://doi.org/10.1016/j.strueco.2020.05.006>
- Wang L, Wang H, Cao Z, He Y, Dong Z, Wang S (2022a) Can industrial intellectualization reduce carbon emissions? — Empirical evidence from the perspective of carbon total factor productivity in China. *Technol Forecast Soc Chang* 184:121969. <https://doi.org/10.1016/j.techfore.2022.121969>
- Wang J, Wang B, Dong K, Dong X (2022c) How does the digital economy improve high-quality energy development? The case of China. *Technol Forecast Soc Change* 184:121960. <https://doi.org/10.1016/j.techfore.2022.121960>
- Wang J, Dong K, Dong X, Taghizadeh-Hesary F (2022b) Assessing the digital economy and its carbon-mitigation effects: The case of China. *Energy Econ* 113. <https://doi.org/10.1016/j.eneco.2022.106198>
- Wen H, Wen C, Lee C (2022) Impact of digitalization and environmental regulation on total factor productivity. *Inf Econ Policy* 61:101007. <https://doi.org/10.1016/j.infoecopol.2022.101007>

- Wu H, Xue Y, Hao Y, Ren S (2021) How does internet development affect energy-saving and emission reduction? Evidence from China. *Energy Econ* 103:105577. <https://doi.org/10.1016/j.eneco.2021.105577>
- Yao X, Zhang X, Guo Z (2020) The tug of war between local government and enterprises in reducing China's carbon dioxide emissions intensity. *Sci Total Environ* 710:136140. <https://doi.org/10.1016/j.scitotenv.2019.136140>
- Yi M, Liu Y, Sheng MS, Wen L (2022) Effects of digital economy on carbon emission reduction: New evidence from China. *Energy Policy* 171:113271. <https://doi.org/10.1016/j.enpol.2022.113271>
- Zhanbayev R, Bu W (2023) How does digital finance affect industrial transformation? *J Inform Econ* 1:18–30. <https://doi.org/10.58567/jie01010002>
- Zhang X, Wan G, Zhang J, He Z (2019) Digital Economy, Financial Inclusion, and Inclusive Growth. *Econ Res J* 54:71–86
- Zhang L, Mu R, Zhan Y et al (2022) Digital economy, energy efficiency, and carbon emissions: Evidence from provincial panel data in China. *Sci Total Environ* 852:158403. <https://doi.org/10.1016/j.scitotenv.2022.158403>
- Zhang Z, Feng Y, Song R, Yang D, Duan X (2021) Prevalence of psychiatric diagnosis and related psychopathological symptoms among patients with COVID-19 during the second wave of the pandemic. *Global Health* 17. <https://doi.org/10.1186/s12992-021-00694-4>
- Zhao T, Jiao F, Wang Z (2023) Digital economy, entrepreneurial activity, and common prosperity: Evidence from China. *J Inform Econ* 1:59–71. <https://doi.org/10.58567/jie01010005>
- Zhou X, Tang X (2022) Spatiotemporal consistency effect of green finance on pollution emissions and its geographic attenuation process. *J Environ Manag* 318:115537. <https://doi.org/10.1016/j.jenvman.2022.115537>
- Zhou X, Tang X, Zhang R (2020) Impact of green finance on economic development and environmental quality: a study based on provincial panel data from China. *Environ Sci Pollut Res Int* 27:19915–19932. <https://doi.org/10.1007/s11356-020-08383-2>

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