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How Does the Digital Economy Affect Carbon Emissions? Evidence from Panel Smooth Transition Regression Model

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Abstract
This essay uses the panel smooth transition regression (PSTR) model to study how China's digital economy affects carbon emissions, selects data from 30 provinces in China during 2011–2021, and constructs a digital economy evaluation index system for empirical analysis. As a nonlinear model, the PSTR model can more accurately reveal the linkage between the digital economy and carbon emissions. Compared with other nonlinear models, this model can obtain the conversion rate of different influence intensities in the digital economy. According to findings, digital economic growth has a significant curbing influence on carbon emissions. But as it advances to a certain point, this inhibiting impact weakens. Furthermore, the digital economy's expansion could boost technological advancement, foreign direct investment, urbanization, and industrial structure optimization to curb carbon emissions in the early stage. Similarly, with the development of the digital economy to a certain extent, this inhibitory effect will weaken or increase. With China promoting a low-carbon economy against the backdrop of the contemporary internet age, it is essential to comprehend the effects of the digital economy on carbon emissions.

Keywords Digital economy · Carbon emissions · Panel smooth transition regression model · Nonlinear effect

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Introduction

The term "digital economy" encompasses an array of economic operations. It treats data information as a fundamental input of production, utilizing computers and the internet as crucial carriers and employing information and communication technologies to enhance productivity and upgrade economic structures (Zou et al., 2024). With the expansion of e-commerce, digital services, data analytics, and intelligent systems, the digital economy has emerged as a primary force driving regional development. For example, the digital economy has enabled high-quality development of export trade in China's eastern coastal areas by enabling export technologies (Liang & Tan, 2024).The digital economy transcends spatial and temporal limitations, accelerates factor mobility, and facilitates the transformation and upgrading of economic development patterns (K¨orner et al., 2022; Wang & Shao, 2024). Moreover, the widespread adoption of digital technologies has significantly improved human life (Palmieri et al., 2024), providing greater convenience and choices through digital channels (Wang & Zhou, 2023), aiding in better decision-making processes (He et al., 2024a, 2024b), and creating numerous job opportunities within the digital industry. Therefore, fostering the development of the digital economy is critically important for both governments and residents, necessitating collaborative efforts from all stakeholders.

The current state of ecological problem brought on by climate issues is still very dire, and global warming has an impact on the long-term sustainability of human civilization (Xu et al., 2024a, 2024b, 2024c). In response to this challenge, there is a global consensus on the crucial importance of controlling carbon dioxide emissions and improving the ecological environment. Many countries have taken action by formulating and implementing emission reduction plans, such as the carbon emissions trading systems in the European Union and Norway (Fæhn & Yonezawa, 2021), carbon taxes in various states in the United States (Arent et al., 2022), and renewable energy subsidies in the European Union and Australia (Degirmenci & Yavuz, 2024). China is the world's top carbon emitter, releasing more than 600 million tons of carbon dioxide annually. Its economic development has a significant impact on total global carbon emissions (Xu et al., 2024a, 2024b, 2024c). China has implemented various measures, including establishing carbon emissions trading markets in cities such as Beijing and Shanghai, to continually advance the development of a low-carbon economy (Wang et al., 2024a, 2024b). But the challenge of increasing carbon emissions on a global scale remains largely undiminished. To this end, taking China as a research object to understand digital decarbonization will not only help countries around the world achieve sustainable development but also be of great significance to the global response to climate change.

However, although the digital economy can affect greenhouse gas emissions, there is no consensus on the relationship between them and the path of impact. This study aims to explore how the digital economy impacts carbon emissions. Existing literature suggests that the digital economy can exert certain effects on climate improvement through economic digitalization (Kurniawan et al., 2024). Industrial digitalization involves empowering traditional industries with digital technologies, fostering new industries, formats, and models, and promoting comprehensive and chain-wide green and low-carbon transformation and upgrading of traditional industries (Li and Hou., 2024). Additionally, the digital economy can suppress carbon emissions through resource allocation efficiency. Moreover, the digital economy promotes carbon reduction through optimized urban management and enhanced urban greening efforts (Cugurullo et al., 2024). Conversely, the increased demand for electricity driven by digital development is a significant factor contributing to carbon emissions growth. Empirical tests have been conducted in some studies using panel data from Chinese cities, revealing that digital economic development significantly stimulates increased electricity consumption (Lin & Huang, 2023). Furthermore, the construction of digital facilities often requires substantial input of physical resources, generating significant carbon dioxide emissions in the process.

There are several major limitations in the existing literature. First, a considerable portion of the literature, including the aforementioned ones, is based on a linear perspective when examining the emission reduction effects of the digital economy. In fact, the impact of digital economy on carbon emissions itself has a certain complexity, rather than a simple and purely linear impact relationship. Secondly, even if some literature uses methods such as panel threshold models to study problems beyond linear perspectives, they still face the problem of abrupt or jumping discontinuities (Han et al., 2022; Wang et al., 2024a, 2024b; Zhang et al., 2023). The impact of the digital economy will not experience a sudden change at any point in time, which seriously deviates from the reality. In fact, smooth transitional changes are more reasonable. Moreover, most literature focuses on the energy structure optimization and energy efficiency improvement effects of the digital economy when examining the impact path (Dong et al., 2024; Xin et al., 2024). The innovation effects, investment effects, urbanization effects, and industrial upgrading effects triggered by digital development may be more significant.

In order to overcome the main limitations mentioned above, this paper takes the data of 30 provinces in China from 2011 to 2021 as the research sample and uses the PSTR model to study the nonlinear relationship among the digital economy and carbon emissions. The panel smooth translation regression (PSTR) model (González et al., 2005) is a suitable method that can be used to verify the nonlinear effect and impact path of digital economy expansion on carbon dioxide emissions. Moreover, the PSTR model can more effectively address the issue of jumping between the initial and final thresholds in the Hansen panel threshold model, which differs from the nonlinear approach utilized in the previous studies. The model can be made to progressively shift with the change variable by including a continuous transformation function, more closely in accordance with actual economic life (Xie et al., 2020). The primary contributions of this study in comparison to earlier research are as follows.

Firstly, this essay reveals a non-linear effect between the digital economy and carbon emissions. The link between the digital economy and carbon emissions has become a focus of scholars, who mostly rely on linear or traditional threshold models, which can lead to deviations from reality. This study uses the PSTR model, which not only allows the examination of nonlinear interactions between the two connections but also provides the speed of transformation of the digital economy development impact path, more accurately reflecting the actual situation.

Secondly, this paper conducts research on four aspects: technological innovation, foreign direct investment, urbanization, and industrial structure optimization, which allows it to thoroughly evaluate the implications of digital economy development on carbon dioxide emissions. For supporting the development of a global low-carbon economy, understanding the impact of digital economy development on greenhouse gas emissions is a crucial reference point. However, most of the current articles look at impact pathway from a single perspective, ignoring its diversity. In addition, we have verified the robustness of variable selection by substituting explanatory variables. A static panel model is also used to compare the results to confirm the robustness of the nonlinear model output.

The remainder of this essay is split into the sections that follow: The literature and research hypotheses are suggested in the "Literature Review and Research Hypothesis" section; the "Methodology and Data" section explains the setting of the PSTR model, the digital economy indicator measurements, and data sources; the "Results" section reports the empirical results; the "Discussion" Sect. 5 discusses the results; and conclusions and recommendations for countermeasures are provided in the "Conclusion and Policy Implications" section.

Literature Review and Research Hypothesis

The Direct Influence of the Digital Economy on Carbon Emissions

Regarding the relationship between the digital economy and carbon emissions, due to the complexity of the digital economy itself, a straightforward response to this topic is challenging to provide. On the one hand, the government's real-time monitoring of emissions into the atmosphere is technically supported by the use of big data and satellite-based sensing (Kaginalkar et al., 2021); the use of low-carbon technology companies by the digital economy can help increase production factors' efficiency and resource allocation (Li et al., 2023). The digital transformation of non-digital enterprises will optimize business processes, improve management efficiency and stimulate innovation, thereby enhancing the competitive advantage of enterprises in the market (Onesi-Ozigagun et al., 2024). To meet the goal of energy efficiency and decarbonization, enterprises can also create matching carbon emission reduction strategies based on the information offered by big data (Zhang et al., 2022a, 2022b). The dissemination, creation, and sharing of information across time and space are all benefits of big data platforms. People's digital tendencies or digital channels will also promote sustainable consumption (Palmieri et al., 2024). The development of electric vehicles can make transportation sustainable and thus reduce CO2 emissions (Deng et al., 2024).

On the other hand, the growth of Internet infrastructure is essential for the digital economy's progress, but maintaining data processing and storage in cloud computing and data centers calls for a significant quantity of electrical supply (Coyne & Denny, 2021; He et al., 2024a, 2024b). Power supply still mainly relies on the use of fossil energy at this stage, and the electricity production process in power plants will produce large amounts of carbon dioxide (Kartal et al., 2024). The convenience of transactions made possible by the rise of the digital economy would also encourage the tertiary industry's expansion. The development of service industries such as tourism may lead to more use of cars and other means of transportation, which may also lead to more carbon emissions and traffic congestion (Ye et al., 2024). The development of digital economy makes online shopping more efficient, which may lead to more manufacturing and processing activities; these activities may need to consume more raw materials and fossil energy (Mutezo & Mulopo, 2021; Song et al., 2024a, 2024b); the digitization of the production process may also lead to more production and logistics activities, which will result in a boost in carbon dioxide emissions (Barreto et al., 2017).

All of the above literature highlights only the one-way impact of the digital economy, which is to either reduce or increase carbon emissions. Obviously, the influence relationship between the two is not monotonous, and there is probably a complex nonlinear relationship between the two. Therefore, there may be some deviation in the conclusions obtained from the linear research method used in the above literature. When studying the relationship between economic development and environmental pollution, the environmental Kuznets curve (EKC) has attracted widespread attention, and some academics have confirmed the inverse U-shaped association involving carbon emissions and economic progress (Guo & Shahbaz, 2024; Liu et al., 2022). According to the study, the digital economy may also produce changes in how it alters carbon emissions. As a result of the analyses shown above, Hypothesis 1 is suggested:

> Hypothesis 1: There is a nonlinear link between the growth of the digital economy and carbon emissions, and the development of the digital economy generally suppresses carbon dioxide emissions.

Indirect Impact Pathways of the Digital Economy on Carbon Emissions

Technological innovation The development of digital technology has generated a large amount of data, including user behavior data, social media data, and sensor data. These data can be used for model training and optimization, promoting the rapid development of artificial intelligence, big data, and cloud computing (Ge et al., 2024). For enterprises, this may optimize production processes and promote green production (Tan et al., 2024). For example, studies have shown that AI can reduce the carbon footprint of cement manufacturing enterprises by optimizing electricity consumption (Pan et al., 2024). Meanwhile, the digitalization may encourage business investment and Research and Development (R&D) in enterprise that focus on protection of the environment and reduced carbon technologies (Sun et al., 2024). In addition, enterprises can use big data analysis to discover new market demands and drive product and service innovation. Utilizing digital platforms can promote resource sharing and reuse, which is conducive to forming an active innovation ecosystem (Lafuente et al., 2024). The digital economy is expanding quickly, and more and more companies are beginning to focus on lowering carbon emissions and developing solutions that safeguard the environment (Litvinenko, 2020). For enterprises, technological innovation eliminates wasteful resource use and excessive energy consumption during manufacturing to accomplish energy conservation and carbon reduction (Borowski, 2021). The framework of technical innovation affecting carbon emissions in the digitalization has generally been the subject of current studies, but they are all predicated on a linear approach.

Foreign direct investment A rise in domestic production and efficiency because of the digital economy has the potential to attract Fdi inflows. New technologies and business models have emerged on account of the expansion of the digital economy, which will open up new market opportunities and encourage Fdi inflows (Zhang & Wang, 2024). The effect of foreign direct investment on carbon emissions has always been an important issue. As a developing country, the impact of Fdi on carbon emissions in China is either "pollution paradise" or "pollution halo," at this stage of research, no unified conclusion can be drawn. To meet their national emission reduction goals, developed countries shift high-pollution and high-energy businesses to developing nations through the use of foreign direct investment (Liu & Wei, 2022; Song et al., 2024a, 2024b). Developing countries may cut carbon emissions by acquiring cleaner industrial technology and practices from established countries, and the growth of emerging economies has rendered them a significant focus of global foreign direct investment (Ikram et al., 2021; Viglioni et al., 2024). The research findings in the available literature are therefore inconsistent regarding the question of whether foreign direct investment might act as an intermediary variable in the digital economy's effect on carbon emissions.

Urbanization Most scholars have reached a consensus that digital development can promote urbanization, but there is still some debate on whether urbanization can promote carbon emission reduction. Through digital communication, high-quality resources and services from cities can be radiated to surrounding rural areas, promoting integrated urban–rural development (Zhang et al., 2024). Scholars also concentrate on the connection involving urbanization and carbon emissions. According to studies, as urbanization progresses, the intensity of CO_2 emissions will decline (Xu et al., 2024a, 2024b, 2024c). Digital development will empower intelligent urban management, and intelligent management systems based on big data and the Internet of Things will promote the construction of green cities and improve the quality of urban ecological environment (Cugurullo et al., 2024). However, urbanization may also promote carbon emissions. Literature has found through research on multidimensional urbanization that urbanization has a significant positive impact on carbon emissions. For example, land urbanization often occupies a large amount of green space and agricultural land, leading to a weakened natural carbon sink function and an increase in carbon emissions. Population and economic urbanization can lead to the concentration of high-energy consuming industries and the "heat island effect," which can alter local climate and indirectly affect carbon emissions (Wu et al., 2024).

Industrial structure upgrade The digital advance often promotes industrial transformation in various industries (Wang & Li, 2024). Digital industrialization has the potential to raise the share of the tertiary industry that uses little energy and emits little pollution, as well as to lower transaction costs and boost transaction efficiency (Luo et al., 2022; Tan et al., 2024). Additionally, the digital industrial revolution that brought about the digital economy has also given rise to the number of emerging industries, the bulk of which are in the technology sector and have relatively low emissions (Wang & Chen, 2024). A decrease in the amount of fossil energy consumed across the industrial supply chain will naturally result in a drop in carbon emissions when the industry with low energy consumption becomes the leading industry (Ghorbal et al., 2024). The enhancement of a digital economy might lower carbon dioxide emissions by boosting the industrial structure.

We propose the following hypothesis in light of the aforementioned analysis:

> Hypothesis 2: Technological innovation, foreign direct investment, urbanization and industrial structure optimization can become indirect impact pathways of digital economy development to curb carbon dioxide emissions, and the impact poses particular effect at different stages.

Methodology and Data

PSTR Model

Model Setting

The PSTR model put forth by González et al. (2005) is used in this essay. The PSTR model is an extension of the smooth transition model (STR) and panel threshold model (PTR). It replaces the discrete transition functions in the PTR model by introducing continuous transition functions, so that the model coefficients can continuously change with the change of transformation variables (Pan et al., 2021). Because of this, the model can solve the jump before and after the threshold in the panel threshold model more efficiently. Meanwhile, the model is appropriate towards multi-section data analysis and successfully represents both smooth transformation and the variability between various sections. Hence, compared with the traditional model, the PSTR model can better reflect the heterogeneity of data cross section and time. Therefore, compared with the traditional model, the PSTR model can better reflect the heterogeneity of data cross section and time. Before employing this approach, it is necessary to perform nonlinear testing, also known as the testing of the feasibility and validity of PSTR model. The samples are then separated into two categories, low regime and high regime, depending on the stage the digital economy is at. By comparing the coefficients of low and high regimes, it is possible to judge whether there is an indirect mechanism for the effect on CO2 emissions of the digital economy's progress. The model is constructed as follows:

$$CEit=\alpha i+\beta X_{it}+\sum_{j=1}^{m} g(Digit;\gamma j, cj)\times \phi X_{it}+\varepsilon it \tag{1}$$

CE_{it} represents the carbon dioxide emission intensity of province i in year $t\alpha_i$ represents the individual effect, $X_{it}=(Dig_{it}, Ti_{it}, Fdi_{it}, Urb_{it}, Iup_{it}, Fin_{it}, Ins_{it}, Inc_{it})$ represents the value of each explanatory variable and control variable in province t in year $i\beta=(\beta_1,\beta_2,\beta_3,\beta_4,\beta_5,\beta_6,\beta_7,\beta_8)$, and $\phi=(\phi_1,\phi_2,\phi_3,\phi_4,\phi_5,\phi_6,\phi_7,\phi_8)$; the measurement method and selection of variables are in the "Data" and "Variable Choice" sections making an introduction. According to the method of Inglesi-Lotz et al. (2018), the conversion function $g(Digit;\gamma j, cj)$ is defined as follows:

$$g(Digit;\gamma j, cj)=\frac{1}{1+\exp[-\gamma j\prod_{j=1}^{m}(Digit-cj)]} \tag{2}$$

where γ is the smoothing coefficient, or slope coefficient, of the conversion function. The slope of the transfer function increases as γ increases, indicating a faster rate of transmission between various regions.

The panel threshold model may be used in place of the PSTR model where $\gamma\to\infty$. The PSTR model transforms into a linear regression model when $\gamma\to 0$. cj represents a positional parameter. Additionally, the model setting must choose the values of the crucial parameters r and m. r stands for how many conversions there are. The model has $r+1$ regions when the total amount of transition functions is r, and when $r=1$, there are two states, low and high regime. The conversion function positional parameters are represented by the letter m. In the case of $r=1$ and $m=1$, the variance range involving ϕ is $[\beta,\beta+\phi]$; in the case of $\beta>0$ and $\beta+\phi<0$, the relationship between the explanatory variable with the variable being explained has an inverted U shape.

Test Model Feasibility

It is necessary to confirm the viability of the PSTR model before starting empirical research. From a qualitative perspective, the relationship between digital economy and carbon emissions tends to become increasingly complex. Traditional panel data models such as fixed effects and random effects models typically assume linear relationships among variables, which is not realistic. PSTR model can capture the complex dynamic structures present in the data, accommodating non-linear features. Some non-linear models, such as panel threshold model, can capture state changes, but they often exhibit abrupt transitions and require predetermined threshold points or other critical parameters. This tends to introduce subjectivity among researchers, leading to biased research outcomes. In contrast, the PSTR model offers greater flexibility by automatically identifying transition points in the data and estimating model parameters through methods like maximum likelihood estimation, thereby reducing subjective biases and aligning more closely with empirical realities. Clearly, selecting the PSTR model is more suitable for our study. From a quantitative perspective, a non-linear effects test must be performed first. The PSTR model cannot be determined if the data are linear. Next, ascertain a suitable value for m. Finally, the nonlinear least squares (NLS) are used to obtain the parameters. In reference to González et al. (2005), set the null hypothesis as $H_0 : \gamma = 0$. The first step is to perform Taylor series expansion on $g(Dig;\gamma, c)$ at $\gamma = 0$, as shown in Eq. (3):

$$CE_{it} = \alpha i + \phi_0{\prime} X_{it} + \phi_1{\prime} X_{it} q_{it} + \cdots + \phi_m{\prime} X_{it} q_{it}^m + \varepsilon_{it}^* \tag{3}$$

where $\varepsilon_{it}^* = \varepsilon_{it} + R_m \phi_1{\prime} X_{it}$, the remaining Taylor expansion is R_S, and $H_0^* : \phi_0{\prime} = \phi_1{\prime} = \cdots = \phi_m{\prime} = 0$ is used as the null hypothesis. Acceptance of the null hypothesis indicates that the model exhibits linear characteristics. Otherwise, this model is considered to have obvious nonlinear effects, and the PSTR model can be used. Normally, verifying H_0^* can be achieved by testing the values of LM, LMf, and LRT. These metrics are calculated as follows:

$$LM = \frac{TN(SSR_0 - SSR_1)}{SSR_0} \sim \chi_{mk}^2 \tag{4}$$

$$LMf = \frac{(SSR_0 - \frac{SSR_1}{sk})}{\frac{SSR_0}{TN-N-mk}} \sim F(mk, TN - N - mk) \tag{5}$$

$$LRT = -2[\ln(SSR_1/SSR_0)] \sim \chi_{mk}^2 \tag{6}$$

In this paper, we mainly examine the nonlinear characteristics by observing LMf. In a linear panel model with individual effects, SSR_0 is the squared residual sum. The two-mechanism PSTR model's abbreviation SSR_1 stands for the sum of squares of the residuals. The total amount of parameters for the model is indicated by k, and the time dimension is denoted by T. There are considerable nonlinear effects and at least one transition function if H_0^* is not accepted. The larger the value of LMf, the more suitable the quantity of m. Sequential testing can be done to choose the best r value when the number of $g(Dig;\gamma, c)$ is established.

Operation Process

A linear model has been estimated in the first step, and the estimated model is checked on nonlinear effects. If the linearity presumption is disproved in the second phase, the number r of transformation functions is minimum equivalent to 1. Choose a two-regime PSTR model to perform estimation before moving on to the following phase. If not, keep the linear model's estimated result. In the third step, the residual nonlinearity of the model is tested. A multi-regime PSTR model with $r = 2$ is estimated if the null hypothesis is shown to be not accepted. When nonetheless, the analysis moves on to the next phase. The aforementioned actions are repeated in the fourth phase until no more nonlinear tests pass the first time. The steps of the PSTR are shown in Fig. 1.

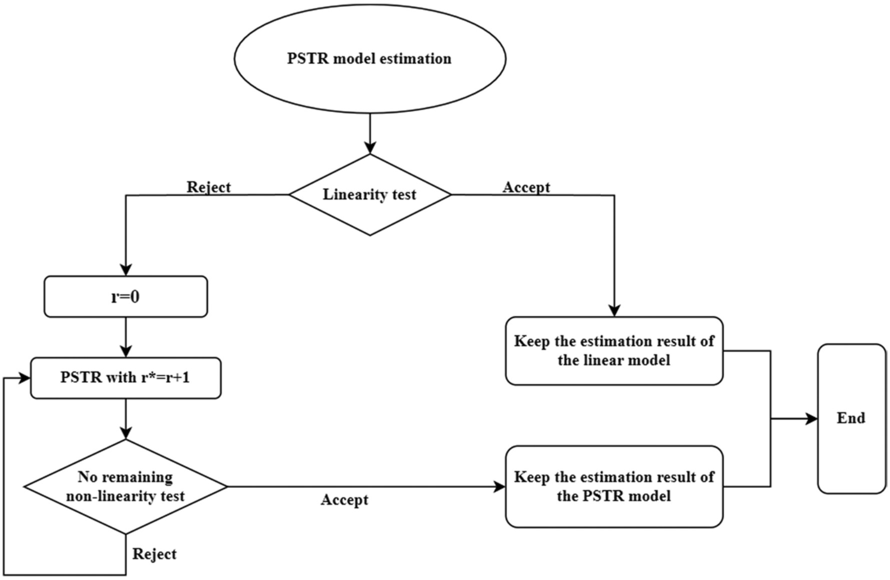

Fig. 1 PSTR model operation process

Data

Data Sources

This essay primarily examines the indirect effects of the growth of the digital economy on the level of carbon dioxide emissions. This essay chooses panel data for the time frame of 2011 to 2021 across 30 Chinese provinces (Tibet is not included owing of a data shortage). In statistics, if a sufficiently large random sample is drawn from a population and these samples reflect to some extent the diversity and variation within the population, then reasonable estimates of the population can be derived through statistical inference. China's provincial-level sample data are typically comprehensive and detailed, encompassing various economic activities and sources of carbon emissions, thus exhibiting strong representativeness. Provincial samples not only illuminate the overall trends in China's digital economy development and carbon emission reduction but also highlight regional disparities in policy implementation and economic development path choices, thereby offering insights into the overall situation in China.

The National Bureau of Statistics, different provincial statistics yearbooks, and the Digital Finance Research Center of Peking University provided the sub-index data required to build the digital economy development index. Total annual CO_2 emissions data for each province used to calculate carbon intensity is taken from carbon emission accounts and datasets (CEADs). The National Bureau of Statistics, the China Energy Statistical Yearbook, the China Statistical Yearbook, and the EPS database provide the majority of the data for the other explanatory variables.

Calculation of the Digital Economy

The measurement method of the digital economy has not yet reached a consensus. Based on the literature research (Liu et al., 2020; Pan et al., 2022), combined with an understanding of the concept of the digitalization and the availability of relevant data, the index of 30 provinces is calculated all across from 2011 to 2021. The corresponding secondary indicators are chosen from the four aspects of digital infrastructure, digital user application, digital industry development, and digital innovation to build an indicator system in China. The indicators selected for the comprehensive system of the digital economy are displayed in Table 1.

The entropy weight method is selected as the measurement method. Its advantage is that it can reflect the information of the data itself, with less human intervention and strong objectivity. The entropy weight method determines the index weight by using information entropy, and the operation process is not cumbersome and can avoid subjective deviation within a certain range, and the accuracy and authority of the result are high. Based on practical considerations, the measurement and computation of the weights of numerous indicators of the digital economy are better suited to the entropy weight law. The precise calculation process starts with the following:

The first thing to do with the entropy weight method is dimensionless the initial data. Due to the wide coverage of the index system, the data units and dimensions are different. The effect of various dimensions upon that measurement weight should be minimized, it is necessary to dimensionless the indicators deal with. In this study, we use the range normalization method to process the original matrix dimensionless, and the processing methods are shown in Eqs. (9) and (10). For the

Table 1 Digital economy indicator system

Level 1 indicators	Level 2 indicators	Attributes
Digital infrastructure	Optical cable length (km/km^2)	+
	Number of domain names (10,000)	+
	Number of pages (10,000)	+
Digital user application	Number of internet broadband access ports (ten thousand)	+
	Mobile phone penetration (department/hundred people)	+
	Coverage breadth of Financial Inclusion Index (−)	+
	Depth of use of Financial Inclusion Index (−)	+
	Degree of digitalization of Financial Inclusion Index (−)	+
Digital industry development	Software business revenue as percentage of GDP (%)	+
	Proportion of employees in the information industry (%)	+
	Total telecom business per capita (100 million yuan)	+
Digital innovation	Technology market turnover as a percentage of GDP (%)	+
	Full-time equivalent of Research and Development (R&D) personnel in industrial enterprises above designated size (−)	+
	Research and Development (R&D) expenditure of industrial enterprises above designated size as percentage of GDP (%)	+

positive index data, the larger the value, the better; Eq. (9) is used to process the data; for the negative index data, that is, the smaller the better index data, Eq. (10) is used to process the data.

$$X = \begin{bmatrix} x_{11} & x_{12} & \dots & x_{1n} \\ x_{21} & x_{22} & \dots & x_{2n} \\ \dots & \dots & \dots & \dots \\ x_{m1} & x_{m2} & \dots & x_{mn} \end{bmatrix} \tag{7}$$

$$X\prime = (X_{ij}\prime)_{mn} \tag{8}$$

$$X_{ij}\prime = \frac{X_{ij} - \min(X_j)}{\max(X_j) - \min(X_j)} \times 6 \tag{9}$$

$$X_{ij}\prime = \frac{\max(X_j) - X_{ij}}{\max(X_j) - \min(X_j)} \times 6 \tag{10}$$

Within each of the m evaluation objects, $\max(X_j)$ represents the jth index's highest value, while $\min(X_j)$ represents the jth index's lowest value. The value of the data after dimensionless processing is between 0 and 6.

Calculate the eigenvalue weight Pij and information entropy ej of each index, as shown in Eqs. (12) and (13):

$$P_{ij} = \frac{X''_{ij}}{\sum_{i=1}^{m} X''} \tag{11}$$

$$e_j = -\frac{1}{\ln(m)} \sum_{i=1}^{m} P_{ij} \ln(P_{ij}) \tag{12}$$

Determine the entropy weight Wj and the corresponding entropy weight value Dig_{ij} for each indicator, as shown in Eqs. (14) and (15):

$$W_j = \frac{1 - e_j}{\sum_{j=1}^{n} 1 - e_j} \tag{13}$$

$$Dig_{ij} = W_j \times X_{ij}\prime \tag{14}$$

Bring the found data into Eqs. (7)–(14) to determine the entropy weights of each indicator of the digital economy spanning 2011 to 2021. The findings are presented in Table 2, where it is clear that the first-level indicators of the digital economy are weighted in the following order: digital infrastructure, digital innovation, digital industry development, and digital user application. In addition, the weights of the number of webpages and the proportion of technology market turnover in GDP are

Table 2 Weights of digital economy indicator system

Level 1 indicators	Level 2 indicators	Weights	
Digital infrastructure	Optical cable length (km/km^2)	0.0932	0.3616
	Number of domain names (10,000)	0.1027	
	Number of pages (10,000)	0.1657	
Digital user application	Number of internet broadband access ports (ten thousand)	0.0730	0.1456
	Mobile phone penetration (department/hundred people)	0.0186	
	Coverage breadth of Financial Inclusion Index (−)	0.0202	
	Depth of use of Financial Inclusion Index (−)	0.0181	
	Degree of digitalization of Financial Inclusion Index (−)	0.0157	
Digital industry development	Software business revenue as percentage of GDP (%)	0.0948	0.2507
	Proportion of employees in the information industry (%)	0.0693	
	Total telecom business per capita (100 million yuan)	0.0866	
Digital innovation	Technology market turnover as a percentage of GDP (%)	0.1159	0.2421
	Full-time equivalent of Research and development (R&D) personnel in industrial enterprises above designated size (−)	0.0969	
	Research and development (R&D) expenditure of industrial enterprises above designated size as percentage of GDP (%)	0.0293	

relatively prominent, accounting for 0.1505 and 0.1143, respectively. The weights of the three sub-indices of the Peking University Inclusive Finance Index, the coverage breadth, the depth of use, and the degree of digitalization, are relatively small, none of which exceeded 0.019.

Variable Choice

Explained Variable

Carbon intensity (CE): this paper uses carbon emission intensity to measure the annual CO_2 emission level of each province and calculates the ratio of the regional CO_2 emissions to the real GDP.

Explanatory Variables

Digital economy development index (Dig) The comprehensive index is determined according to the entropy weight method and includes four first-level indicators that can objectively reflect the digital economy's growth level in various provinces.

Technological innovation (Ti) This article measures technological innovation by taking the logarithm of the amount of patent grants in each province. Technological innovation can lead to improved energy efficiency and production capacity, which can promote the development of low-carbon economy. This paper does not use the number of patent applications in each province to measure technological innovation, because the number of applications reflects the willingness of individuals or enterprises to innovate technology. However, the number of granted patents serves as a metric that can more accurately indicate the degree to which technology innovation is occurring.

Foreign direct investment (Fdi) This essay applies the methods of Ji and Zhang (2019) and Ouyang and Li (2018) to measure Fdi as a ratio of Fdi to GDP. In the studies of many scholars, the impact of Fdi on environmental pollution is not uniform. On the one hand, it is believed that foreign direct investment will introduce high-energy-consuming and high-polluting enterprises into the region, causing pollution to the regional environment; on the other hand, it is believed that foreign direct investment will produce technological spillover benefits, improve energy utilization efficiency, strengthen the international flow of production factors, stimulate businesses' capacity for production, boost resource distribution effectiveness, and achieve carbon emission reduction.

Urbanization (Urb) This study measures the degree of regional urbanization by comparing the permanent urban population to the overall permanent population. Enhancement in urbanization will have a profound effect on carbon dioxide emissions (Xie et al., 2019). The increase of urbanization rate would greatly benefit the pooling and allocation of regional resources, which can stimulate the maximization of resource efficiency and fully demonstrate the scale advantage.

Industrial structure upgrade (Iup) The suitable industrial structure is measured in this study using the ratio of the tertiary industry's added value to the total of the secondary and primary industries' added values. Xu and Tan (2020) point out that the advanced industrial structure measures the trend of advanced structural adjustment and the transformation of economic agents to knowledge- and technology-intensive industries.

Control variables In this paper, financial development (Fin), institutional quality (Ins), and economic growth (Inc) were selected as the control variables. Some scholars believe that the impact of financial development on carbon emissions is bidirectional. It can not only increase carbon dioxide emissions by promoting economic expansion but also reduce carbon emissions through technological innovation and structural improvement. In addition, there is a significant negative relationship between institutional quality and carbon emissions, indicating that efficient and fair domestic institutions are essential to promote carbon emission reduction (Salman et al., 2019). Finally, based on the study of Jiang and Yu (2023), it is not difficult to find that economic growth also have an impact on carbon emissions. Table 3 displays the descriptive statistical findings for each variable.

Results

The existence of threshold effects has to be investigated in order to establish that the PSTR model is better than the traditional linear regression model when analyzing the effect of the digital economy on the carbon emission pathway and to guarantee the PSTR model's viability. Before using NLS methods to estimate the coefficients and parameters of the PSTR model, this essay needs to determine the number of transfer functions and thresholds.

Threshold Effect Test

Before using the PSTR model, the first thing is verified the presence of thresholds. Table 4 displays the test results. According to the results of Table 4, the result of Fisher's test is 6.296 at $m = 1$, greater than 5.102 at $m = 2$, rejecting the null hypothesis of linear effect at a significance level of 1%, and confirming the nonlinear relationship, based on comparing AIC and BIC values, it can also be found that it is more appropriate to choose one transfer function. In addition, the value of LMf is 1.376 at $m = 1$, H0 : $r = 1$ and the P value is higher than 0.1. There may be differences in implications for carbon emission intensity in places with varying degrees of the digital economy. The amount of location parameters should indeed be adjusted to 1, as the expansion of the digital economy may have two different consequences, according to the research above. The model contains a transfer function $g(Dig;\gamma, c)$ and a transition position ($m = 1$ and $r = 1$). In conclusion, it is suitable and robust to utilize the PSTR model when evaluating how the digital economy affects CO_2 emissions.

Table 3 Descriptive statistics

Variable	Definition	Mean	Std. dev	Min	Max
CE	Total CO_2 emissions/real GDP	2.139	1.747	0.192	10.448
Dig	Calculated by entropy weight method	0.130	0.104	0.012	0.701
Ti	Number of patents granted	10.135	1.635	4.796	13.679
Fdi	Foreign direct investment/real GDP	0.019	0.015	0.000	0.080
Urb	Urban population/total population	0.059	0.121	0.350	0.896
Iup	Tertiary industry added value/(secondary industry added value + primary industry added value)	1.009	0.702	0.485	5.147
Fin	Loans and deposits in financial institutions/real GDP	3.395	1.088	1.678	7.578
Ins	Measured by marketization index	7.993	1.909	3.360	12.922
Inc	The natural logarithm of real GDP	5.570	2.905	1.602	18.398

Table 4 Test of the threshold effect in the PSTR model

	$m=1$	$m=2$	$m=1$
	H0: linear model	H0: linear model	H0: $r=1$
	H1: $r\geq 1$	H1: $r\geq 1$	H1: $r\geq 2$
Wald tests (LM):	48.372 (0.000)	73.674 (0.000)	12.658 (0.124)
Fisher tests (LM_f):	6.296 (0.000)	5.102 (0.000)	1.376 (0.207)
LRT tests (LRT):	52.307 (0.000)	83.371 (0.000)	12.907 (0.115)
AIC	0.268	0.303	-
BIC	0.475	0.521	-

The values in the parentheses are the *P* values. *, **, and *** denote the statistical significance at the 10%, 5%, and 1% levels, respectively

Parameter Estimation

The model's parameters can be calculated, and the outputs are displayed in Table 5 after verifying the existence of thresholds and choosing the perfect number of transition functions and thresholds. The inflection moment c in the model is 0.1584, which is apparent in Table 5. As a result, regions in the low regime are those with the Digital Economy Development Index below 0.1584,

Table 5 Estimated results of the PSTR model

Variables	β	φ
Dig	−12.1532***	9.3978***
	−2.9139	2.6083
Ti	−0.6091***	0.5466***
	−7.0854	3.4508
Fdi	−50.9336***	87.7181***
	−7.9098	5.5070
Urb	11.5269***	−18.4259***
	5.6355	−5.7079
Iup	−3.8273***	3.9044***
	−5.4393	5.7156
Fin	−0.0824	−0.0115
	−0.3724	−0.0661
Ins	0.2037	−0.1119
	1.6009	−1.1662
Inc	−0.0574	0.0449
	−0.5655	0.3515
c	0.1584	
γ	27.0246	

The values underneath the values in each row are the *t*-values. *, **, and *** denote the statistical significance at the 10%, 5%, and 1% levels, respectively and other regions are those in the high regime. Moreover, a conversion rate γ between low and high levels is provided by the PSTR model. The γ values in the model are 27.0246, which means a quick transition from the low to the high regime. This shows that when the level of development of the digital economy reaches a critical point, its influence will shift quickly. Positive effects on carbon emission reduction, or a dampening effect on carbon emission intensity, are indicated by negative coefficients for the variable. The values of β and $\beta + \phi$ are the coefficients of the explanatory variables for carbon emission intensity in the low and high regime of the digital economy, respectively. The following is a thorough explanation of how the digital economy's growth has affected environmental quality.

Firstly, its coefficient of Dig within the low regime is − 12.1523, while within the high regime model, it is − 2.7545 (− 2.7545 = − 12.1523 + 9.3978), demonstrating that the digital economy can inhibit the intensity of carbon emissions in both the low and high regimes. This effect is more pronounced when the digital economy is in its early stages of development. The following is analysis of the various indirect paths:

Promote technological innovation The coefficient for TI under the low regime is − 0.6091, and the result is significant at the 1% level. It means that technological innovation cannot significantly reduce carbon dioxide emission intensity in areas that have low levels of digital economy. But its coefficient reaches − 0.0625 under the high regime, and its level of significance also reaches 1%. This shows that when the development of the digital economy reaches a certain level, technological innovation can reduce the intensity of greenhouse gas emissions. As the development of the digital economy drives the development of the platform, the funds required for innovation can be raised through more channels. The development of the digital economy has brought sufficient financial support to the technological innovation of individuals and enterprises, reducing the worries of innovative talents and enterprises.

Attracting foreign direct investment Foreign direct investment can reduce carbon emission intensity in provinces with a low level of digital economy, as shown by the coefficient of Fdi within that low regime of the model, which is − 50.9336 and is very significant. However, as the digital economy advances, its coefficient of Fdi within that high regime changes to 36.1745, a significant value at the standard of 1% that demonstrates foreign direct investment can effectively control climate quality and encourage carbon dioxide emission reduction. The inflow of foreign direct investment, accompanied by pollution transfer, technology transfer and structure transfer, has a complex impact on China's carbon emissions. Therefore, the inflow of foreign direct investment within a certain scale may show a "pollution halo" effect in China as a whole, that is, it reduces carbon emissions, and will show the opposite effect after reaching the inflection point.

Promote urbanization In the low regime, the Urb coefficient is 11.5269, which is significant at the 1% level. Its coefficient in the high regime is − 6.8990, which is

1% significant. It demonstrates that encouraging urbanization can significantly cut carbon dioxide emissions as the digital economy develops. Urbanization means the agglomeration of talents, capital, and other factors that provide human conditions for the development of the modern service industry. Urbanization promotes the agglomeration of service industries and the enhancement and effectiveness of industrial structures in the interest of lowering carbon emissions. In addition, there are economies of scale in climate control, so the spatial agglomeration caused by urbanization can help reduce carbon emissions.

Support the advanced industrial structure The coefficients of Iup in low regime and high regime are − 3.8237 and 0.0807, respectively, which means that in the low regime where the development of the digital economy is underdeveloped, the advanced industrial structure will decrease the carbon emission intensity. The impact of industrial structure on the intensity of carbon emissions will vary, nevertheless, as the digitalization's degree of development rises. Although the advanced industrial structure has a positive impact on climate quality, this effect will wane with the growth of the digital economy. The negative impact of advanced industrial structure on carbon emission intensity gradually tends to level off with the development of industrial digitalization and digital industrialization.

Robustness Test

Analysis of Group-Level Regression

For the low and high regime situations in this section, the conventional linear panel regression model is also used to verify the robustness of the regression method. The inflection moment for the Digital Economy Development Index (Dig), which is used in this study to gauge the growth of the digital economy, is 0.1584 in Table 5. The regions are separated into two regimes based on the aforementioned positional factors. The remaining 60% of the provinces are categorized as low regime, except 8 locations, including Beijing, Tianjin, Shanghai, Zhejiang, Jiangsu, Fujian, Shandong, and Guangdong, which have high developmental status in the digital economy. Table 6 displays the outcomes of the static panel regression model.

Panel models containing fixed and random effects are shown in Table 6 as FE and RE, respectively. At the 1% level, the F-statistic's two values are both significant. As a result, the mixed regression model is disregarded, whereas based on the Hausman test results, a model with fixed provinces is used in the low region and a model with random effects is used in the high regime. First, the coefficients of Dig are significantly negative at the levels of 5% and 1%, respectively, as indicated in Table 6, which is consistent with the outcomes of the PSTR model. Second, the coefficients of TI are negative in both regimes, and the significance level reaches 1% in the low regime. This shows that the improvement of the level of scientific and technological innovation can have a good inhibitory effect on carbon emissions with the digital economy develops. Third, the coefficients of Fdi and Iup are significantly negative in the low regime and significantly positive in the high regime, which means that with the development of the

Table 6 Estimation results of low and high regime

Variables	Low regime		High regime	
	FE	RE	FE	RE
Dig	−10.9822**	−4.5622	−3.3860***	−2.0451***
	4.9516	2.8593	0.8854	0.7308
Ti	−0.7397***	−0.0054	−0.0080	−0.0580
	0.1031	0.0787	0.0655	0.0618
Fdi	−36.1323***	−2.1827	13.8550***	10.5823***
	7.8776	4.7188	2.9206	0.5033
Urb	10.1595***	−3.3097	−3.6809***	−3.4261***
	1.7751	2.3561	0.5291	0.5033
Iup	−4.9905***	−0.3259	0.2044**	0.0736
	0.7695	0.3732	0.0796	0.0638
F-statistic	13.51***		12.85***	
Hausman test	92.85***		8.56	

The values underneath the values in each row are standard errors. *, **, and *** denote the statistical significance at the 10%, 5%, and 1% levels, respectively

digital economy, the carbon emission reduction effect of both will gradually decrease until it disappears. This is also exactly consistent with the estimated results of the PSTR model. Finally, with regard to urbanization, the results show that digital economic growth can reduce carbon emissions by increasing urbanization rates. In summary, the results obtained by the PSTR model are robust.

Test for the Robustness of Variable Selection

In order to confirm the robustness of variable selection, this paper uses the number of research and development investment projects (R&D) to represent technological innovation and uses the industrial structure advanced (Iad) index to measure the industrial structure optimization in the PSTR model. The number of R&D projects and the original data for calculating Theil index come from the National Bureau of Statistics, Regional Statistical Yearbook, and Science and Technology Statistical Yearbook. The regression results are shown in Table 7. As shown in Table 7, the development of the digital economy can curb carbon dioxide emissions by supporting technological progress and can also improve climate quality by promoting urbanization. The variation of the coefficient of Iad is the same as that of Iup, which verifies the robustness of variable selection.

Discussion

There has been a considerable amount of interest in the connection between the growth of the digital economy and carbon emissions, but the research on this subject is still subject to controversy. The rise of the digital economy can give businesses

Table 7 Estimated results of the robustness test of variable selection

Variables	β	φ
Dig	−34.2731***	29.7380***
	−4.0683	3.8253
R&D	−0.4558**	0.6933**
	−2.4885	2.4864
Fdi	−62.0526***	80.8500***
	−5.3450	4.0646
Urb	18.9677***	−22.3205***
	6.0637	−5.8025
Iad	−2.5936***	2.8290***
	−5.9940	5.1154
Fin	0.0348	−0.1695
	0.1348	−0.6457
Ins	0.0682	0.1404
	0.4658	1.0401
Inc	−0.2438	0.2171
	−1.4212	1.0685
c	0.0586	
γ	14.2482	

The values underneath the values in each row are the t-values. *, **, and *** denote the statistical significance at the 10%, 5%, and 1% levels, respectively

and governments technical assistance to make life more convenient for citizens. With progress in the digital economy's level, the government's real-time monitoring level of climate change has been improved, and the platform of the carbon emission trading market has been improved (Liu et al., 2015). In addition, the production efficiency, resource allocation efficiency, and energy utilization efficiency of enterprises have been continuously improved, so that carbon dioxide emissions have been controlled and low-carbon economic development has been continuously promoted (Huang et al., 2022; Wang et al., 2019). Although some studies have found that the digital economy can have a restraining effect on carbon emissions, they are all based on a linear perspective, and in real life, this effect is not necessarily a completely linear relationship. Therefore, there are still controversies in the existing literature on the effect analysis and mechanism analysis of this topic. In this paper, the nonlinear model of PSTR is used for empirical research, which is more in line with the actual situation. According to the empirical results, the hypothesis proposed in this paper has been verified.

First, hypothesis 1 is verified, and there is a nonlinear link here between growth of the digital economy and carbon emissions. In accordance with the findings of our study, the growth of the digital economy can initially have a considerable inhibition on the intensity of carbon emissions, but once regional digital economies develop to a certain degree, their inhibitory effects on carbon emission intensity start to wane. Digital technology was integrated into the traditional process of production during the beginning phases of the digital economy's development, which may have improved the production efficiency of traditional production (Zhang et al., 2022a, 2022b). The use of digital technology may also increase the effectiveness of resource allocation and energy use, which can support the decrease in greenhouse gas emissions. As a result, when the digital economy grows, the carbon dioxide emissions' intensity may be drastically decreased in the early phases of development (Ma et al., 2022). Nevertheless, the efficiency of energy conservation and emission reduction brought on by the digitalization of its industry declines as the development of the digital economy reaches a certain level. Infrastructure development will, to some extent, limit the promotion of digital industrialization (Peng et al., 2023). Moreover, as the digital economy grows in scope, more fossil fuels will need to be used to maintain the supply of electricity, which will result in higher carbon emissions. Notwithstanding, the digital economy as a whole continues to support initiatives aimed at lowering carbon emissions. E-commerce has also grown significantly as a result of the expansion of the digital economy. The increase in online shopping will lead to the development of the postal industry (Jaag, 2014), which is one of the possible causes of the carbon emission reduction program's waning effectiveness at this mature phase of digital economy development.

Furthermore, by boosting technological innovation, enhancing foreign direct investment, encouraging urbanization, and optimizing the industrial structure, the growth of the digital economy can decrease greenhouse gas emissions, hypothesis 2 is verified to the test.

(1) According to our research results in Table 5, technological innovation cannot have a direct negative impact on carbon emissions in regions where the development of the digital economy is low, but due to the development of the digital economy can promote that the channels for raising funds for innovation are increased, and corresponding financial support is provided. Therefore, improvements are made in energy and production efficiency, as well as in the willingness of people to innovate, and carbon emissions are also controlled.

(2) When the digital economy is still in its initial stages of growth, foreign direct investment can help with the effort to reduce carbon emissions. At the stage, the carbon emission reduction effect of foreign investment may benefit from the effect of technology transfer, but with the continuous improvement of digitalization, this positive effect is gradually weakened to negligible. At this time, the continuous increase of foreign investment not only does not reduce carbon emissions, but also may increase carbon emissions due to its pollution transfer effect (Wang et al., 2021).

(3) In the initial phases of digital development, urbanization has a detrimental effect on carbon emissions, and as the digital economy develops further, the urbanization effect becomes stronger. The expanding digital economy has the potential to make cities more appealing and to close the gap between urban and rural areas. As urbanization levels have increased, so too have inhabitants' understanding of low-carbon living.

(4) By enhancing the industrial structure, the digital economy can also control the intensity of carbon emissions. Thus, according to the results in Table 5, improv-

ing the industrial structure does directly result in an inhibition in carbon emissions, but as the degree of the digital economy rises, the benefit of the advanced industrial structure on carbon emissions tends to be negligible. It may be because the tertiary industry has lower energy consumption compared with the primary and secondary industry. However, with economic growth, carbon emissions from the tertiary industry will also increase (Begum et al., 2015). As a corollary, the percentage of tertiary industry is increasing, which still helps decrease greenhouse gas emissions.

Conclusion and Policy Implications

The investigation of the impact of the expansion of the digital economy on carbon emissions is extremely vital in terms of how digital China and low-carbon development complement one another. This analysis evaluates the level of digital economy development in 30 provinces over the period of 2011 to 2021 in China and examines how this growth has affected carbon emissions. For the sake of empirical study, a panel smooth transition regression model is created. Several robustness tests are then test on the data. The exploration came to the following conclusions.

First, the impact of digital economy development on carbon emissions generally showed a restraining effect, but there was a nonlinear effect. Initially on, the rise in the digital economy can drastically decrease carbon emissions. But, as the level of the digital economy rises, this reduction effect weakens. It can be observed that as the level of the digital economy approaches the threshold, there is a smooth transition in its impact, with the carbon emission reduction effect of the digital economy decreasing rapidly. Second, the digital economy significantly mitigates carbon emissions by fostering technological innovation and urbanization. Specifically, as the digital economy advances, technological innovation consistently reduces carbon emissions across all scenarios, while the carbon reduction impact of urbanization manifests beyond a certain threshold. Moreover, the effect of digital economy on greenhouse gas emission reduction by stimulating foreign investment and promoting industrial transformation is significant in the early stage, but as the level of digital economy reaches the threshold, this positive effect will weaken or even disappear.

These findings inform the following recommendations and countermeasures that this article makes, first, the government should encourage the development of the digital economy in regions where it is currently underdeveloped. For example, increasing financial support to reduce barriers to research and development of low-carbon technologies and providing clean energy subsidies to create a low-carbon economy. Second, while developing the digital economy, it is essential to strengthen its use in various industrial sectors. For example, encourage big data, cloud computing, and other industries to integrate, improve the efficiency of resource utilization in the secondary and tertiary industries, and strengthen the suppression of carbon emissions. Third, it is necessary to minimize wasteful energy use, make full use of a new generation of information technology to monitor the energy use of base stations in real time, and optimize the energy consumption effect brought about by the expansion of the digital economy, so as to reduce greenhouse gas emissions.

In this essay, the nonlinear relationship and influence mechanism of the growing digital economy upon carbon emissions are discussed. However, more work needs to be done in the future, and the digital economy evaluation index system requires further enhancement. Besides, due to all the difficulties in gathering data, it is impossible to obtain more recent data for empirical testing, and as discussed in the article, whether the impact of the mechanism will change as the digital economy continues to develop deserves further discussion.

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Declarations

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