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RESEARCH ARTICLE

The impact of digital economy on total factor carbon productivity: the threshold effect of technology accumulation

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Abstract
This research focuses on the impact of the digital economy on total factor carbon productivity. Based on the panel data of China's provinces from 2009 to 2019, this paper incorporates undesired output, namely carbon emissions, into the evaluation index system, and uses the SBM-ML index to measure regional total factor carbon productivity, and uses the RAGA-PP model to measure the digital economy development index, which includes three dimensions: digital infrastructure, digital industry development, and digital economic environment. Moreover, this paper incorporates the heterogeneous threshold of technological accumulation into the framework of the impact mechanism of total factor carbon productivity and builds a threshold model to examine the impact of the digital economy on total factor carbon productivity under different technological accumulation thresholds. The research shows that, first, during the sample period, total factor carbon productivity fluctuated around the frontier, showing a certain upward trend, with significant regional heterogeneity. Second, the digital economy has a promotional effect on the total factor carbon productivity level in China and can become the new energy for the country to improve the level of green development. Third, the impact of the digital economy on total factor carbon productivity presents a significant heterogeneous threshold effect of technological accumulation, along with the increasing level of technology accumulation, the effective coefficient of the digital economy on total factor carbon productivity is increasing, and the level of significance is increasing. Last, the low-carbon driving mechanism of the digital economy has temporal and spatial heterogeneity of regional technology accumulation levels. The conclusions of this paper provide an effective reference for exploring the realization mechanism of regional total factor carbon productivity improvement, ecological civilization construction, and high-quality economic development.

Keywords Digital economy · Technology accumulation · Total factor carbon productivity · Threshold model · Temporal and spatial heterogeneity

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Introduction

As the most dynamic sector in China's economic development, the digital economy refers to a new economic form that leads the high-quality economic development based on digital knowledge and information. In this process, economic entities will realize optimal allocation and regeneration of resources under the promotion of emerging technologies such as the Internet and information communication (Ojanper et al., 2019; Ding, 2020). The digital economy, whose essence is informatization, possesses the characteristics of remarkable speed, high permeability, externality, and sustainability (Jing and Sun, 2019; Amuso et al., 2020).

The digital economy plays a vital role in stimulating consumption, boosting investment, and creating jobs (Zhao et al., 2020). From a domestic perspective, according to the relevant data in the "Blue Book of Digital Economy: Frontiers of China's Digital Economy (2021)" issued by the Chinese Academy of Social Sciences, the added value of China's digital economy was 19.14 trillion yuan in 2020, which account for about 18.8% of GDP, showing a sustained and rapid growth momentum. During the 14th Five-Year Plan period, China's digital economy is expected to maintain rapid growth momentum in "digital industrialization" and "industrial digitization," with a nominal growth rate of 11.3. And by 2025, the added value of China's digital economy will reach 32.67 trillion yuan (nominal); from an international perspective, according to the "Global Digital Economy White Paper," the scale of the global digital economy in 2020 reached 32.6 trillion dollars, a year-on-year increase of 3%. The USA and China are considered key leaders in this field. China's digital economy has maintained rapid growth and gradually become essential for high-quality economic development. As General Secretary Xi Jinping put forward, it is necessary to "make the digital economy bigger and stronger to create a new carrier of innovation-driven strategy." Therefore, effectively releasing the boosting force of the digital economy for China's high-quality development is of great significance, which has become an active topic widely discussed by the government and all sectors of society in recent years.

The integration of the digital economy with economic and social fields is expanding in both breadth and depth, exerting a profound impact on production and lifestyle (Sun, 2020). The impact of the digital economy on the national economy is reflected not only in the scale of the output value of the digital industry but also in the effect of the digital economy on improving economic quality and efficiency, that is, its impact on productivity (Viollaz 2019). However, previous studies have only focused on allocating traditional production factors such as capital and labor in the digital economy. For example, the digital economy can generate economies of scale through network externalities, thereby reducing marginal costs for businesses (Chen et al., 2020). Wang (2020) pointed out that in promoting industrial transformation and upgrading, the digital economy characterized by intelligence has had a significant impact on the labor market and reshaped the employment structure of China's labor force. Against the backdrop of climate warming and ecological environment deterioration, the world has substantially entered the stage of low-carbon development. Hence, it is a necessary and urgent research topic to incorporate carbon emissions into the allocation efficiency of production factors and explore the low-carbon driving effect of the digital economy (Han. 2021).

Kaya and Yokobori proposed the concept of carbon productivity in 1997. Since it combines the dual objectives of controlling carbon emission levels and promoting economic growth, it is widely recognized as an effective measure of productivity in the context of sustainable development (Guo and Luo, 2016). At the historical intersection of the "carbon peak and carbon neutral" strategy and the development of the digital economy, China, as major global energy consumption and carbon emission emitter, shoulders a greater responsibility in accelerating the layout of green and low-carbon industries. Based on this, we hold the following question. Does the development of the digital economy increase China's carbon productivity? If the effect is confirmed, what are the mechanisms behind it? In addition, given China's regional heterogeneity, what are the regional differences in the impact of the digital economy on carbon productivity? These are urgent scientific questions to be solved.

The digital economy is inherently highly technical (Xiao et al. 2019). On the one hand, based on the theory of the techno-economic paradigm, the digital economy relies on modern information networks and flexible manufacturing systems to break the traditional Fordist mass production paradigm (Wang and Chen, 2019). Only in an application environment that is biased towards the development trajectory of technological revolution can the role of the climate shaper of the techno-economic paradigm be effectively played, thereby breaking the inertial resistance of the existing paradigm. On the other hand, the theory of "technology accumulation" points out that the technology gap can significantly restrain the spillover effect of the new economic form (Cantwell and Tolentino 1990). Higher technology accumulation can strengthen the resource allocation effect of the digital economy and promote the optimization and integration of supply chain management, thereby contributing to the improvement of overall productivity. On this basis, technological accumulation plays an important role in the relationship between the digital economy and total factor carbon productivity growth, pointing out this paper's direction, which the existing research has paid little attention to.

The innovations and contributions of our research are as follows. For one thing, in terms of research perspective, we examined the factors that influence the regional total factor carbon productivity from the standpoint of the digital economy; For another thing, in terms of research methods, we have extended theoretical methods and empirical methods. In theoretical analysis, we applied the theory of network information economy to sort out the mechanism of the digital economy on total factor carbon productivity. And in the empirical research, we first adopted the Malmquist-Luenberger index, which contained the undesired output to measure the change rate of total factor carbon productivity through data envelopment analysis. Then, we selected the threshold regression model to examine the network effect of the digital economy affecting regional total factor carbon productivity.

The rest of this paper is organized as follows. The second part sorts the relevant literature and proposes research hypotheses. The third part discusses empirical methods and illustrates the data. The fourth part reports the results of the empirical analysis. The fifth part is the robustness test. The sixth part summarizes the research conclusions and expounds on the research deficiencies and prospects.

Literature review

As the digital economy gradually becomes an essential part of national economic activities, scholars have focused on the digital economy to improve the quality of economic growth and promote sustainable development. By sorting out relevant literature, this paper establishes the following three parts of literature that are closely related to research: (i) the connotation and effect of digital economy, (ii) the connotation and influencing factors of total factor carbon productivity, (iii) literature on the digital economy, technology accumulation, and total factor carbon productivity.

The connotation and effect of the digital economy

The connotation of the digital economy

The study of the digital economy is regarded as an open system that is in its infancy. At present, there is no complete definition of the digital economy in academic circles. Don Tapscott (1996) first proposed the digital economy in his book "*The Digital Economy*." He believed that the flow of information was presented physically in the traditional economy, while in the new economy, information evolved into a digital form, which provided evidence that the digital economy was equivalent to the new economy or knowledge economy. The G20 Hangzhou Summit defined the digital economy as a series of economic activities to improve efficiency and optimize the economic structure, with digital knowledge and information as key production factors, modern information network as an important carrier, and effective use of information and communication technology as the essential driving force. Scholars have different understandings of the digital economy due to the integration degree of ICT and industry (Aral et al., 2012; Li, 2019). For instance, Bukht and Heeks (2017) divided the digital economy into three layers: The first layer was the digital field, including hardware manufacturing, software, and I.T. consulting; and the second layer was the narrow-caliber digital economy, including electronic business, digital services, and platform economy; the third layer was the broad-caliber digital economy, including e-commerce and algorithm economy.

In a narrow sense, the digital economy mainly involves turning data into an industry: digital industrialization (Guo and Lian, 2020). Digital industrialization refers to some traditional industries in the industrial classification of the national economy, including the communication equipment manufacturing industry, Internet industry, software, and information technology service industry. Thus, digital industrialization corresponds to the first layer by the division of Bukht and Heeks (2017), that is, the digital field.

In a broad sense, the digital economy includes the deep integration of digital technology with the traditional economy and the real economy, that is, industrial digitization. Industrial digitalization refers to the application of digital technology in the industry to improve the quantity and quality of products and increase the output of traditional industries. Compared with the division of Bukht and Heeks (2017), industrial digitalization is equivalent to the sum of the second and third layers.

The effect of the digital economy

With the in-depth advancement of supply-side structural reforms, the digital economy has flourished and penetrated all economies and societies. In academia, scholars have focused on the "enabling effect" of the digital economy on economic growth based on both macro and micro levels. It is worth noting that although some literature has discussed the green impact of Internet development and ICT, there is no study focusing on the low-carbon effect of the digital economy.

First of all, scholars have concentrated on the digital economy's scale effect, arguing that the digital economy could exert a significant economic growth effect by reshaping the supply system, enhancing growth potential, and reducing transaction costs. Specifically, this effect has been manifested at all the macro, meso, and micro levels. At the macro level, the digital economy has changed the supply system of production factors, breaking through the constraints of the scarcity of factors and the law of increasing marginal cost under the neoclassical economic system and realizing the scale effect of economic output. Cai and Ma (2021) systematically analyzed the driving role of data elements in promoting high-quality development in the digital economy era based on refining the essential characteristics of elements. Based on the meso-level, the digital economy reconstructed the industrial system, led industrial transformation through industrial digitization and digital industrialization, cultivated new impetus, and opened up new space for economic growth (Berkhout and Hertin, 2004). Gnezdova et al. (2019) pointed out that the continuous integration of industrial digitalization and economic society played a vital role in driving economic development; at the micro-level, the digital economy redefined the trust mechanism in the traditional transaction process, guided the transformation of corporate organizational models, and improved management efficiency. Vu (2013) and Zhang (2019) both proposed that changes in the internal and external environment in the digital economy era would promote profound changes in enterprise organizations' operation and management methods. The organizational model of enterprises would transform into network, flatness, and flexibility.

The connotation and influencing factors of total factor carbon productivity

The connotation of total factor carbon productivity

Under the threat of global warming, carbon emissions have become a non-negligible factor affecting economic and social development. Compared with traditional productivity, carbon productivity has become a research hotspot in academia because it can link economic growth with carbon emissions to seek a balance between economic and environmental development. Kaya and Yokobofi (1997) were the first scholars who put forward the concept of carbon productivity. They defined it as the level of GDP output per unit of carbon dioxide emissions.

The measurement methods of carbon productivity mainly include the single-index and multiple-index methods. According to Kaya and Yokobori (1997) concept, the single-indicator method directly used the ratio of GDP to carbon dioxide emissions to measure carbon productivity. Because of simple structure, convenient measurement, and the linkage between economy and environment, it has attracted widespread attention (Du and Li, 2019). However, some scholars have pointed out the limitations of a single indicator. In contrast, the total factor carbon productivity index system considering various related factors is more suitable for evaluating carbon emission performance since the carbon productivity results from energy consumption and economic development. Many scholars have used the data envelopment analysis (DEA) method to study total factor carbon productivity at the national, regional, and industry levels.

The influencing factors of total factor carbon productivity

As a vital characterization variable for low-carbon economic growth or sustainable development, total factor carbon productivity has been studied by many scholars. At present, there are a lot of studies on the influencing factors of promoting total factor carbon productivity, which is based on different perspectives. Li et al. (2016) proposed that expanding the scale of energy use and improving the factor allocation structure could effectively improve carbon productivity. Cheng LL (2018) and Anser et al. (2020a, b) explored urbanization's spatial and nonlinear effects on carbon productivity, respectively. They both affirmed the vital role of urbanization in promoting carbon productivity, but the effects were heterogeneous. Based on empirical analysis, Liu and Hu (2016) proposed that the impact of foreign direct investment on carbon productivity was manifested as "pollution paradise" and "pollution halo" effects. The foreign direct investment significantly increased carbon productivity in the region but negatively influenced carbon productivity in neighboring areas. Li et al. (2020) analyzed the immediate and spatial spillover effect of heterogeneous environmental regulation on carbon productivity. They found significant differences in the impact of different ecological regulation tools on carbon productivity. Bai and Sun (2021) expounded and empirically tested Internet development's impact mechanism and effect on total factor carbon productivity from cost, innovation, and demand perspectives. It was found that energy structure and energy utilization efficiency were essential factors affecting carbon emissions. Due to the clean characteristics of renewable energy (Alharthi et al., 2021), replacing fossil energy with renewable energy is an effective way to reduce carbon emissions, which is more critical for emerging market countries. Since the rapid economic growth in these countries, the factor-driven reality cannot be changed in the short term (Yang et al., 2021). Hence, they need to develop renewable energy to reduce carbon emissions and increase carbon productivity.

Based on the above analysis, little research has been done on the impact of the digital economy on carbon productivity. This paper believes that the digital economy may have a certain effect on total factor carbon productivity. Specifically, as an environment-friendly industry with minor damage to the ecological environment (Liang et al., 2021), the development of the digital economy can promote the overall increase in carbon productivity by squeezing the traditional economy characterized by high investment, high pollution, and high emissions. Moreover, the digital economy has significant economies of scale, which can change the conventional extensive economic growth model, reduce the dependence of traditional production methods on natural resources and environmental pollution, and promote energy conservation and consumption reduction in the entire industry chain by combining big data supervision and energy Internet (Guire et al., 2012). Finally, the digital economy can build an ecological civilization by establishing environmental feedback mechanisms and spreading the green living concept. Based on the above analysis, this paper proposes the following research hypothesis:

Hypothesis 1: The development of the digital economy will promote total factor carbon productivity.

Literature on the digital economy, technology accumulation, and total factor carbon productivity

Due to the technology-intensive nature of the digital economy, its development requires a high level of technological accumulation (Amri et al. 2019. Although scholars have not directly pointed out that technology accumulation impacts the green development effect of the digital economy, the role of technological accumulation cannot be ignored. Based on the "techno-economic paradigm" and the theory of technological accumulation, Zhang et al. (2018) analyzed the threshold role of technological innovation in the economic effect of the Internet. They pointed out that with the improvement of the level of innovation, the spillover effect of the Internet on economic growth increased, which verified the threshold role of technology accumulation in the Internet economy. At the same time, Wang and Wang (2016) also empirically tested the threshold effect of technological innovation accumulation in breaking the "resource curse." They proposed that in areas where the intersection factor between social capital and technological innovation was more significant than the threshold value, the "curse" effect of resources on economic growth gradually became weak, disappeared, and even turned into a "blessing" in the process. A high level of technology accumulation could enhance the resource allocation effect of the digital economy (Wang and Jing, 2019) and promote the optimization and integration of supply chain management, thereby promoting the growth of overall productivity Xiao et al. 2019). Therefore, this paper combines the digital economy and technology accumulation to explore the heterogeneous role of technology accumulation between the digital economy and total factor carbon productivity growth. The second hypothesis of this paper is as follows:

Hypothesis 2: Technology accumulation plays a threshold role in the impact of the digital economy on total factor carbon productivity.

Based on the above analysis, this paper believes that the digital economy and the "carbon peak and carbon neutral" goal are historical convergence periods. The digital economy is bound to undertake the vital task of promoting the low-carbon economic transformation. At the same time, given the technological complexity of the digital economy as well as the significant regional heterogeneity of China, it is necessary to incorporate technology accumulation into the analysis of the impact of the digital economy on total factor carbon productivity (Fig. 1) and examine the heterogeneous threshold characteristics of technology accumulation on the relationship between the two. We also need to clarify the digital economy's differences, suitability, and dependence in the role of total factor carbon productivity and further explore the realization mechanism of regional low-carbon sustainable development.

Models and variables

Measurement of total factor carbon productivity growth rates

Measurement methods

Traditional carbon productivity is reflected by the ratio of GDP to carbon emissions over the same period. Since it only considers the relationship between carbon emissions and economic output, it is also known as single-factor carbon productivity. DEA, which considers both input and output without setting production function, has been gradually applied to measure carbon productivity (Han 2021). Therefore, in this study, the Malmquist-Luenberger index based on the data envelopment analysis method considering undesired outputs is used to measure the variation of total factor carbon productivity. This approach was first proposed by Chung et al. (1997), and its core idea is to introduce a directional distance function into the measurement.

The directional distance function can be defined as follows. First, determine the set of production possibilities P(x).

$$P_x = \{(y, b) : x \mathrm{canproduce}(y, b)\} \tag{1}$$

$x \epsilon R_+^N, y \epsilon R_+^M, b \epsilon R_+^I$ respectively represent N kinds of inputs, M kinds of outputs, and I kinds of undesired outputs. At the same time, it is assumed that the set of production possibilities satisfies that (i) the output is weakly disposable, (ii) the desired output is freely disposable, and (iii) the desired output is null-joint with the undesired output.

The directional distance function seeks to increase the desired output while being able to reduce the undesired output. Thus, the directional distance function can be expressed under the above assumptions.

$$D^{\circ\rightarrow}\_0(x, y, b; g) = \sup\{\beta : (y, b) + \beta g \in P(x)\} \tag{2}$$

$g = g_y - g_b$ is the direction vector. β is the maximum increase in desired output and the decrease in the undesired output according to the given vectors of input and direction.

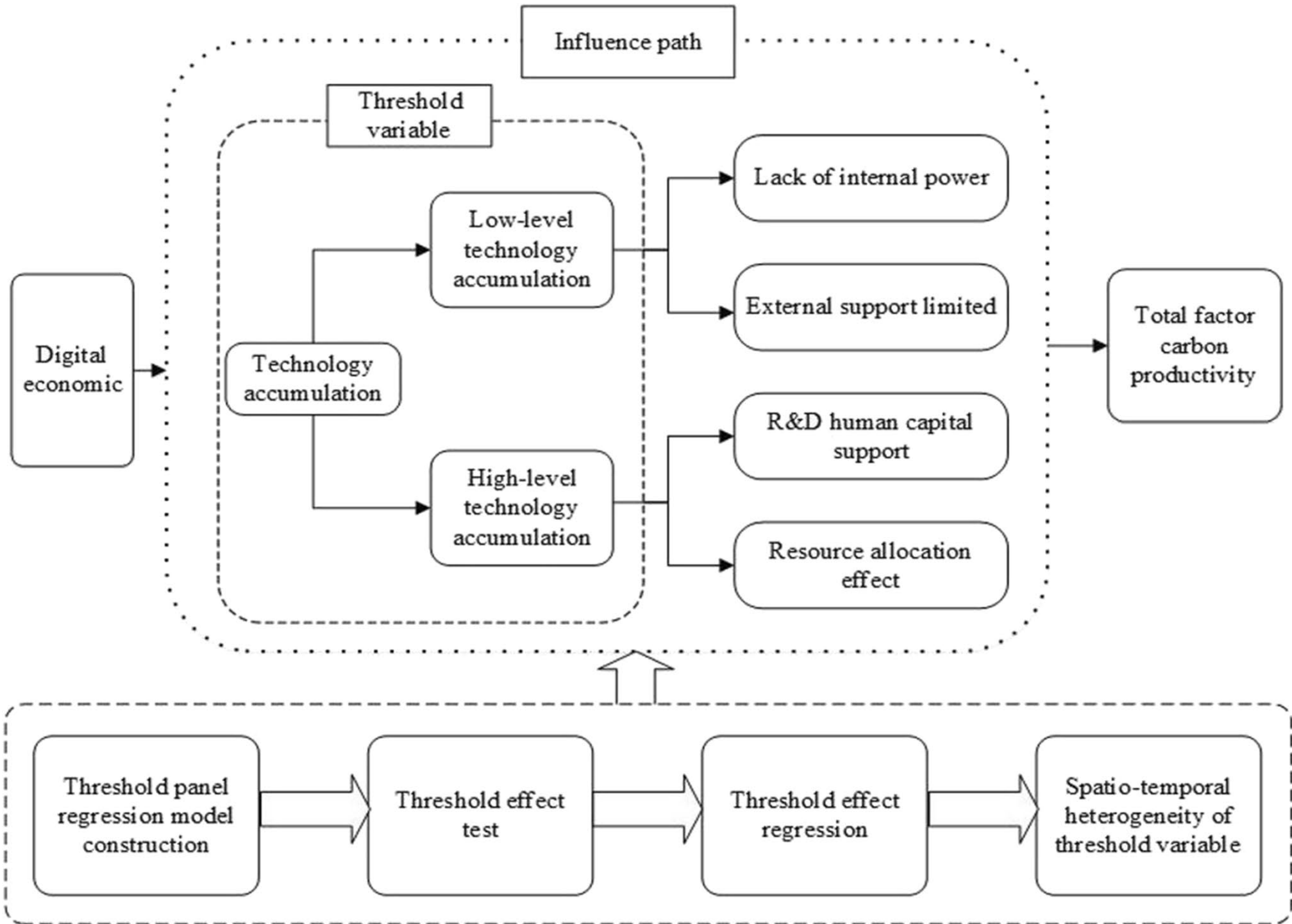


Fig. 1 Main research framework

Based on the directional distance function, Chung et al. (1997) proposed the Malmquist-Luenberger index (ML index for short). The ML index from the period t to period $t+1$ can be expressed as

$$ML_t^{t+1} = \left[\frac{1 + \overrightarrow{D_0^t}(x^t, y^t, z^t, g^t,)}{1 + \overrightarrow{D_0^t}(x^{t+1}, y^{t+1}, z^{t+1}, g^{t+1},)} \times \frac{1 + \overrightarrow{D_0^{t+1}}(x^t, y^t, z^t, g^t,)}{1 + \overrightarrow{D_0^{t+1}}(x^{t+1}, y^{t+1}, z^{t+1}, g^{t+1},)} \right]^{\frac{1}{2}} \quad (3)$$

The ML productivity index reflects the changes in total factor carbon production from the period t to period $t+1$ where the directional distance function can be solved using linear planning. When the ML index is greater than 1, it indicates an increase in productivity; when it is equal to 1, productivity remains constant. When it is less than 1, it means a decrease in productivity. In this paper, we set the total factor carbon production for the base period at 1 and then multiply the measured ML index to obtain the regional total factor carbon production for 2011–2019.

Selection of indicators

The input indicators in our research include physical capital input, human capital input, and energy input. Among them, (i) the amount of physical capital input (X_1) in each province is estimated by physical capital stock in each region. Drawing on the estimation method of Zhang et al. (2004), the data were calculated using the perpetual inventory method; (ii) the amount of human capital input (X_2) in each province is the labor stock of each area; (iii) the energy input (X_3) of each province is the total energy consumption data of each region, in tons of standard coal.

The output indicators include both desired and undesired outputs. (i) Desired output (Y^g) is the real gross regional product of each province in billions of yuan, for the base period of 2010; (ii) undesired output (Y^b) is the carbon emissions of each province, in tons. Referring to the IPCC methodology, we estimated the carbon emissions from eight energy sources. The input and output indicators for total factor carbon productivity in our research are shown in Table 1.

Table 1 The input and output indicators

Genre	Indicators	Variable name	Unit (of measure)
Input variables	Physical capital input	X_1	Billions of yuan
	Human capital input	X_2	Ten thousand people/year
	Energy input	X_3	Million tons of standard coal
Desired output variable	Real gross regional product	Y^g	Billions of yuan
Undesired output variable	Carbon emission	Y^b	Million tons

Construction of a panel threshold model

This research adopts a panel threshold model to examine the impact of the digital economy on the temporal and spatial variation of total factor carbon productivity growth. The complex change law caused by technology accumulation is analyzed According to Hansen (1999), in panel data $\{y_{it}, d_{it}, x_{it} : 1 \leq i \leq n, 1 \leq t \leq T\}$, i is the individual, t is time, and the following threshold regression model can be constructed.

$$y_{it} = u_i + \varphi_1^{\}} x_{it} I\left(d_{it} \leq \theta\right) + \varphi_2^{\}} x_{it} I\left(d_{it} > \theta\right) + e_{it} \tag{4}$$

where I( ) is the indicative function, d_{it} is the threshold variable, and θ is the threshold value to be estimated. According to the size relationship between the value of the threshold variable and the threshold value, the observation sample can be divided into two parts by the threshold value, with different regression coefficients φ_1 and φ_2 for the different parts of the sample. The panel threshold regression model is to find the threshold that minimizes the residual squared sum by establishing a functional relationship between the residual squared sum and the threshold variable and to test whether the threshold effect is statistically significant using the self-help method (Bootstrap). If more than one threshold exists, the results from the estimation of a single threshold need to be explored and tested one by one until no more statistically significant thresholds exist. In general, the panel threshold model can objectively study the complex patterns between the explanatory variables and the explained variables and avoid the subjective bias in the setting of the threshold value of the traditional method to draw more reliable conclusions.

We set the total factor carbon productivity (Carbon) as the explained variable, digital economy (DE) as the explanatory variable, technology accumulation (TA) as the threshold variable, and urbanization (City), human capital (Human), openness (Open), and clean production capacity (Clean) as the control factors to comprehensively investigate the impact of digital economy on total factor carbon productivity under the heterogeneous threshold of regional technology accumulation. The specific data are described as follows:

(i) Explanatory variable: total factor carbon productivity (Carbon), as calculated above.

(ii) Core explanatory variable: digital economy (DE). At present, China does not publish official data on the digital economy index for each region. Some scholars used a single indicator such as the number of employees in the information industry to characterize the level of the digital economy. However, the digital economy is a complex process, and a single indicator is not sufficient to scientifically reflect the true level of development. Therefore, we built a measurement system based on the three dimensions of digital infrastructure construction, digital industry development, and digital economy environment and used the RAGA-PP model to calculate the interprovincial digital economy-level index.

(iii) Threshold variable: technology accumulation (TA). Technology accumulation refers to the incremental accumulation of knowledge and capability in the production and innovation of enterprises. It is the direct product of organizational "learning," while the number of patents is an important proof of innovation results. Also, there is no time lag in patent applications, and it is less affected by the efficiency and preference of patent offices. Therefore, the number of patents can directly reflect the level of technological innovation of enterprises without external interference. In addition, considering that technological innovation is a stock concept, the technical level in the early stage has an important impact on the technical accumulation in the later stage. Therefore, this paper conducts inventory processing on the number of patent applications and then characterizes the technical accumulation in the region.

(iv) Control variables: A series of controls are taken into account referring to existing studies.

Urbanization (City): We use the ratio of the urban population to the total population of the region to estimate it.

Human capital (Human): In this paper, the more commonly used indicator in current empirical studies, average years of schooling, is used as a proxy variable for human capital. The average years of education in each region is calculated using the proportion of each education level in the population as weights. The formula is as follows.

$$\text{Human} = L_1 * 6 + L_2 * 9 + L_3 * 12 + L_4 * 16 \tag{5}$$

where Human is the level of human capital in the region. L_1, L_2, L_3 and L_4 respectively represent the proportion of residents with primary school, junior high school, senior high school, and tertiary education in the population over 6 years old. Since the statistics published are the educational data of the population aged 6 and above, the average years of schooling of the population aged 6 and above are calculated.

Openness (Open): It is represented by the ratio of total regional imports and exports to GDP as a measure.

Clean production capacity (Clean): We measure the ratio of total industrial final energy consumption to sulfur dioxide generation to represent the regional level of clean production.

Table 2 Descriptive statistics of variables

Variable	Obs	Mean	Std.Dev	Min	Max
Carbon	300	1.0367	0.0865	0.8070	1.9563
DE	300	0.8536	0.3086	0.0487	1.6488
TA	300	11.5534	1.7794	5.9307	15.2382
City	300	0.5706	0.1244	0.3381	0.8960
Human	300	9.0831	0.9285	6.7639	12.7820
Open	300	0.2752	0.3135	0.0127	1.5487
Clean	300	0.9168	3.0069	0.0712	38.2735

Descriptive statistics

The data used in this study are mainly from the China Statistical Yearbook, China Labor Statistics Yearbook, China Environment Statistics Yearbook, and the provincial and municipal statistical yearbooks published by the National Bureau of Statistics.

This paper selects 30 regions in mainland China from 2011 to 2019 (the Tibetan data is missing a lot and is not included in the sample) as the research sample. The original data comes from China Statistical Yearbook, China Energy Statistical Yearbook, Statistical Report on China's Internet Development, and various public statistical information. In this paper, the original data are processed accordingly to improve the accuracy of the estimation. Table 2 shows the descriptive statistics of the variables.

We set the total factor carbon productivity (Carbon) as the explained variable, digital economy (DE) as the explanatory variable, technology accumulation (TA) as the threshold variable, and urbanization (City), human capital (Human), openness (Open), and clean production capacity (Clean) as the control factors to comprehensively investigate the impact of digital economy on total factor carbon productivity under the heterogeneous threshold of regional technology accumulation.

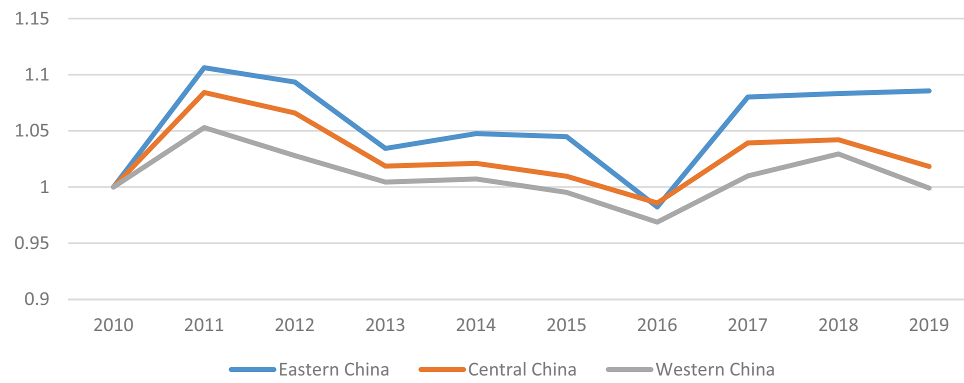
Empirical analysis

Total factor carbon productivity levels in china

In the sample period, the trend of China's total factor carbon productivity is shown in Figure 2. Overall, China's total factor carbon productivity has always fluctuated up and down around the frontier during 2010–2019, showing a certain upward trend. There are significant differences in the level of total factor carbon productivity between different regions. Next, this paper will analyze the evolution trend of total factor carbon productivity during the sample period from the temporal changes and spatial distribution.

On the one hand, in terms of time, (i) there was a significant upward trend in total factor carbon productivity between 2010 and 2011. This can be caused by after the global financial crisis in 2008, the global economy was in the doldrums. In response to the impact, my country has implemented a proactive fiscal policy and moderately loose monetary policies such as interest rate cuts and lending, as well as government investment policies of trillions of yuan to expand domestic demand, promote industrial restructuring, stimulate the economy, and ease employment pressure. While ensuring the smooth operation of the economy, this measure has also attracted a large number of companies with relatively advanced technologies to settle in China, thus enabling my country to achieve a "leap in total factor carbon productivity" in a short period of time. (ii) From 2011 to 2016, total factor carbon productivity showed a fluctuating downward trend, gradually converging to the frontier. Hou (2010) pointed out that the economic crisis provided an opportunity for China to adjust its economic structure and promote industrial upgrading and optimization, showing that China's economy smoothly transitioned from a high-growth, high-energy-consumption, high-pollution development mode to a "new normal" green development mode of medium–low growth, low-energy consumption, and low emissions. (iii) From 2016 to 2018, the total factor carbon productivity showed a steady improvement trend. Which was driven by China's supply-side structural reform and the implementation of new development concepts. In November 2015, General Secretary Xi Jinping proposed to strengthen the supply-side structural reform, focusing on promoting the "three eliminations, one reduction and one supplement." In the same year, the newly revised Environmental Protection Law was officially implemented. At the same time, the Fifth Plenary Session of the 18th Central Committee of the Communist Party of China proposed the concept of green development and incorporated it into the new development concept. The concept of green development has made all

Fig. 2 Total factor carbon productivity level in China



regions take resources and environment as an inherent element of social development and pay more attention to green development. All these have promoted the rapid growth of China's total factor carbon productivity to a certain extent. From 2018 to 2019, in addition to the eastern region maintaining a stable level of total factor carbon productivity, both the central and western regions showed a downward trend. This may be because the economic development of the Midwest depends on industrialization, under the promotion of the "Rise of the Central Region" and the "Western Development" strategy, the central and western regions have achieved rapid economic growth by virtue of energy endowment and resource exploitation, but they have ignored environmental issues to a certain extent (Ji, 2020). With the continuous promotion of my country's high-quality development process, the disadvantages of unreasonable economic structure and insufficient development in the central and western regions have gradually emerged. Therefore, total factor carbon productivity shows a certain downward trend.

On the other hand, when compared at the regional level, similar to the status quo of economic development in various regions in China, total factor carbon productivity also shows a typical spatial distribution of "high in the east and low in the west," which is consistent with the research conclusion of Bai and Sun (2021). Specifically, the level of total factor carbon productivity in eastern regions is significantly higher than that in central and western areas. Firstly, this could be caused by the east part of China having a better foundation for economic development and high-tech industries and high-end manufacturing industries being constantly concentrated in the east part of China, which has an extrusion effect on the energy consumption and pollution-emission-intensive heavy industries. Liu et al. (2021) proposed that the total factor carbon productivity in eastern China is at the forefront of the country because the economic structure of the eastern region is reasonable. For a long time, China's high-tech industries and high-end manufacturing industries have been continuously agglomerating in the eastern region, which has had a significant crowding-out effect on energy-consuming and pollution-intensive enterprises, making it possible for the eastern region to complete the low-carbon transition earlier. However, while the central and western regions continue to undertake the transfer of high-energy-consuming and high-polluting industries in the eastern region, their development is also limited by geographical location, capital, and human capital levels. Hou et al. (2021) calculated the comprehensive level of China's energy dependence and pointed out that the western region of China has not been able to effectively get rid of energy path dependence, the process of industrial structure adjustment is slow, and the efficiency of energy saving and emission reduction is low. Therefore, under the background of the national strategy of regional coordinated development, my country should pay more attention to stimulating the internal driving force of the development of the central and western regions, especially the resource-based regions such as Shanxi and Inner Mongolia. The government should help these regions get rid of the "resource curse" effect, and improve my country's total factor carbon productivity as a whole by cultivating new economic growth points.

Correlation coefficient analysis

From the test results (see Table 3), we can see that the explanatory variables and the explained variables show a strong correlation, basically showing a positive correlation. The correlation between total factor carbon productivity and digital economy and technology accumulation is more obvious.

Variance inflation factor analysis

We used the variance inflation factor (VIF) to test whether there is multicollinearity among the variables, and the test results are shown in Table 4. The largest VIF value among all variables is 7.274, which is less than 10, indicating no multicollinearity among the variables, and the subsequent heterogeneous threshold effect analysis can be conducted (Han 2021).

Table 3 Correlation matrix and summary statistics of variables

Variables	Carbon	DE	T A	City	Human	Open	*Clean*
Carbon	1.000						
DE	0.3674***	1.000					
TA	0.3667***	0.8833***	1.000				
City	0.2999***	0.6489***	0.5051***	1.000			
Human	0.2672**	0.5681**	0.4621**	0.8571***	1.000		
Open	0.2978***	0.4696***	0.3749***	0.7843***	0.6288***	1.000	
Clean	0.2061***	0.3414***	0.2444***	0.3812***	0.4938**	0.2711***	1.000

Note: The statistical values at 10%, 5%, and 1% levels are indicated by *, ** and *** respectively.

Table 4 VIF of each variable

	DE	T A	City	Human	Open	Clean	Average value
VIF	7.27	6.35	4.85	4.44	2.68	1.38	4.49
1/VIF	0.137644	0.157511	0.206263	0.225415	0.373401	0.724787	

Table 5 Results of the threshold effect test

Threshold	F-value	P value	Number of BS	Threshold value		
				10%	5%	1%
Single threshold	40.56***	0.0000	1000	15.2733	18.5725	27.4822
Double threshold	209.36***	0.0000	1000	11.9488	14.6034	20.0455
Triple threshold	25.78	0.7040	1000	56.0009	63.1241	89.6879

Heterogeneous threshold effects

Based on the aforementioned methods, we test the panel threshold model setting with technology accumulation as the threshold variable. That is, the following three sets of hypotheses are tested separately: (i) H_0^I: there is no threshold, H_1^I: one threshold exists; (ii) H_0^{II}: there is only one threshold; H_1^{II}: two thresholds exist; (iii) H_0^{III}: there are only two thresholds; H_1^{III}: three thresholds exist. The results of the tests are shown in Table 5. The single-threshold model passes the test at the 5% level, the double-threshold model passes the test at the 1% level, and the triple-threshold model does not pass the test. Based on Hansen's threshold theory, the model has a double-threshold effect of technology accumulation with thresholds of 13.1863 and 13.2003, respectively (see Table 6).

Then, we demonstrated the estimation results and the corresponding 95% confidence interval construction of the threshold for technology accumulation with the help of likelihood ratio function plots. In Fig. 3 and Fig. 4, when the threshold values are 11.3673 and 11.3736, the LR value of the likelihood ratio statistical test is 0. The corresponding 95% confidence interval is in the original hypothesis acceptance region of the model, and the threshold estimation value is equal to the real value. Therefore, based on the threshold heterogeneity interval, it can be divided into low technology accumulation (TI ≤ 13.1863), medium technology accumulation (13.1863 < TI ≤ 13.2003), and high technology accumulation (TI > 13.2003).

Table 6 Estimated results of the threshold

Threshold	Threshold estimates	95% Confidence interval
Single threshold	13.1863	[13.1465, 13.2003]
Double threshold	13.2003	[13.1863, 13.2132]

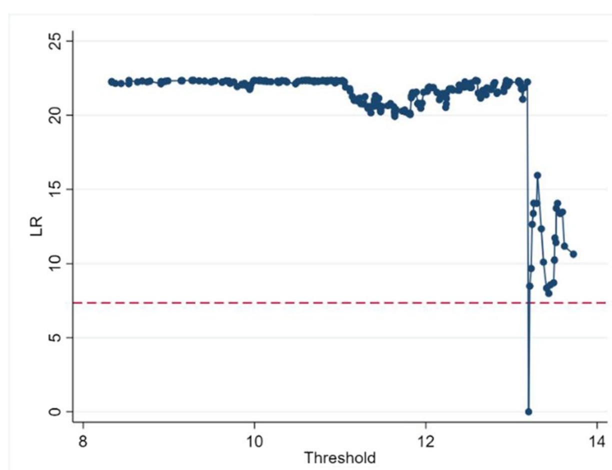


Fig. 3 Single thresholds and confidence intervals

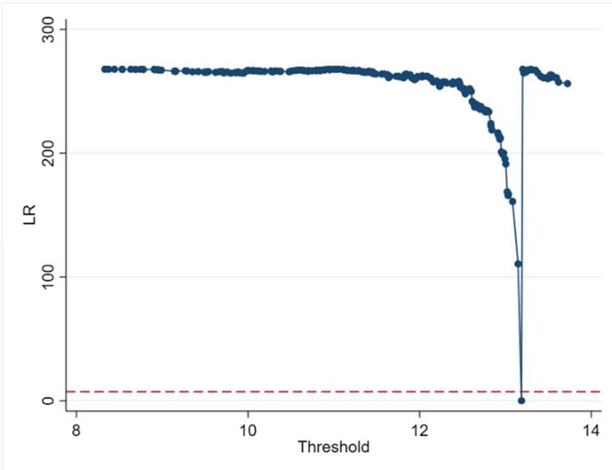


Fig. 4 Double thresholds and confidence intervals

The results of the panel threshold regressions are shown in Table 7.

(i) For the control variables, for every 1% increase in openness, total factor carbon productivity increases by 0.2587% holding other conditions constant. Openness is an important way for China to learn advanced production methods abroad and improve its green development level. Foreign trade exchange can provide more technology samples for China's green development, promote enterprises to acquire advanced knowledge and technology, improve production processes and production efficiency through personnel mobility effect, and thus promote the increase of total factor carbon productivity, which is also consistent with the findings of Song (2021). Therefore, the "driving dividend" of China's opening up to total factor carbon productivity still needs to be deeply explored, and the government should formulate targeted foreign trade policies according to regional differences.

(ii) Clean production has a significant green technological advancement effect and is the main channel for sustainable development. In regions with high levels of pure output, the development and use of new energy sources are supported by technical support, which helps to promote high-end industrial transformation and economic intensification.

(iii) The positive contribution of human capital to total factor carbon productivity has not passed the significance test. The possible reason lies in the irrational allocation of human resources in China, as pointed out by Xie (2019), my country's human capital mismatch is widespread across the country, and the improvement is not large. Compared with the overall optimal human capital allocation level of the economy, most industries in China have different degrees of human resource allocation deviation, especially in high-tech industries and new energy industries, which makes enterprises fail to reach the overall optimal output level and production efficiency of the economy.

(iv) Urbanization has played a significant role in inhibiting the improvement of total factor carbon productivity. We believe that in the rapid urbanization process in China, the emphasis on economic growth and disregard for environmental protection, the focus on growth speed, and the disregard for growth quality ignore the connotative development of urbanization. The one-sided pursuit of economic growth has led to "pseudo-urbanization," which brings great pressure on the environment. This research conclusion is also confirmed by Shao et al. (2019), who pointed out that China's urbanization process is still in the stage of aggravating environmental pollution, so it cannot release the promoting effect of urbanization on total factor carbon productivity.

When technology accumulation is the threshold variable, there is a significant relationship between the digital economy and total factor carbon productivity. When technology accumulation is less than 13.1863, the impact coefficient of digital economy on total factor carbon productivity

Table 7 Results of parameters estimation

Parameters	Coef	Std. Err	t	p > |t|	95% Conf. interval	
City	−0.9831	0.2464	−3.99	0.000	−1.4683	−0.4979
Human	0.0784	0.0189	4.14	0.000	0.0411	0.1157
Open	0.2587	0.0701	3.69	0.000	0.1207	0.3967
Clean	0.0020	0.0019	1.03	0.302	−0.0018	0.0058
DE(TA ≤ 13.1863)	0.0471	0.0415	1.14	0.257	−0.0345	0.1288
DE(13.1863 < TA ≤ 13.2003)	0.0481	0.0856	0.56	0.574	−0.1204	0.2167
DE(TA > 13.2003)	0.1129	0.0416	2.71	0.007	0.0310	0.1947
Cons	0.7571	0.1509	5.02	0.000	0.4599	1.0542

is 0.0471, which does not pass the significance test. When technology accumulation crosses the first threshold, the impact coefficient of digital economy on total factor carbon productivity becomes larger and the significance level increases, but still does not pass the significance test. When technology accumulation crosses the second threshold, the digital economy can positively affect total factor carbon productivity at the significance level of 5%, and the influence coefficient is 0.1129. This shows that with the increasing threshold level of technology accumulation, the impact of the digital economy on total factor carbon productivity increases, and the significance level also increases, showing a significant double threshold effect of technology accumulation.

Discussion on threshold effect regression results

The role of the digital economy in driving total factor carbon productivity growth is constrained by technology accumulation. A low level of technology accumulation cannot highlight the low-carbon effect of the digital economy. Yet it is worth noting that a higher level of technology accumulation can enhance the positive impact of the digital economy on total factor carbon productivity growth. Theoretically, there is a "critical scale" for the positive effect of the digital economy on total factor carbon productivity. Once the technology accumulation has broken through the critical scale, it will raise total carbon productivity by improving regional resource mismatch situation, enhancing energy utilization efficiency, and raising total factor carbon productivity. In other words, the more muscular the regional technical strength, the more pronounced the effect of the digital economy on the structural adjustment of traditional industries will be.

On the one hand, the digital economy drives the endogenous nature of low-carbon economic growth supported by technology accumulation. Technology accumulation is an intrinsic basis and necessary condition for improved production (David et al., 2016). Every step in the R&D, organization, design and manufacturing, display, and marketing require the corresponding accumulation support of technical knowledge. Highly accumulated technologies within the region increase the efficiency of clean production search and selection by firms in the region in the relevant areas, enabling firms to identify the most efficient markets and thus achieve the most optimal carbon productivity. On the other hand, the effect of technological advances inherent in the development of the digital economy can be matched by regional technical accumulation, stimulating firms to make the most of cutting-edge technologies, promoting structural dividends, and increasing carbon productivity.

Spatio-temporal heterogeneity

Table 8 and Fig. 5 show the spatial distribution of high technology accumulation threshold levels from 2010 to 2019. In general, most regions in China have low to medium threshold levels of technology accumulation.

Over time, the number of Chinese provinces located in the high technology accumulation interval has been increasing. In 2010–2011, the whole country was in the low and medium threshold range of technology accumulation. Until 2012, only Jiangsu entered the high technology accumulation level. Since 2013, some developed provinces in the eastern region have gradually entered the high-tech accumulation level, but the progress has been slow. By 2018, there are 13 provinces in the high-tech accumulation range, accounting for less than 50%, limiting the digital economy's green driving role to a large extent. Ganda (2019) proposed that technological innovation is the core driving force for high-quality economic development, and promoting technological progress can help adjust the economic structure and encourage carbon emission reduction. However, China's technological advancement has made a quantum leap (Boeing et al., 2015). However, the quality

Table 8 Spatial distribution of threshold levels for high-tech accumulation

	Eastern region	Central region	Western region	Number
2010–2011	None	None	None	0
2012	Jiangsu	None	None	1
2013	Jiangsu, Zhejiang, Guangdong	None	None	3
2014	Jiangsu, Zhejiang, Shandong, Guangdong	None	None	4
2015	Beijing, Jiangsu, Zhejiang, Shandong, Guangdong	None	None	5
2016	Beijing, Shanghai, Jiangsu, Zhejiang, Shandong, Guangdong	Anhui	None	7
2017	Beijing, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong	Anhui	Sichuan	8
2018	Beijing, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong	Anhui, Hubei, Henan	Sichuan	11
2019	Beijing, Tianjin, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong	Anhui, Hubei, Henan	Sichuan, Shaanxi	13

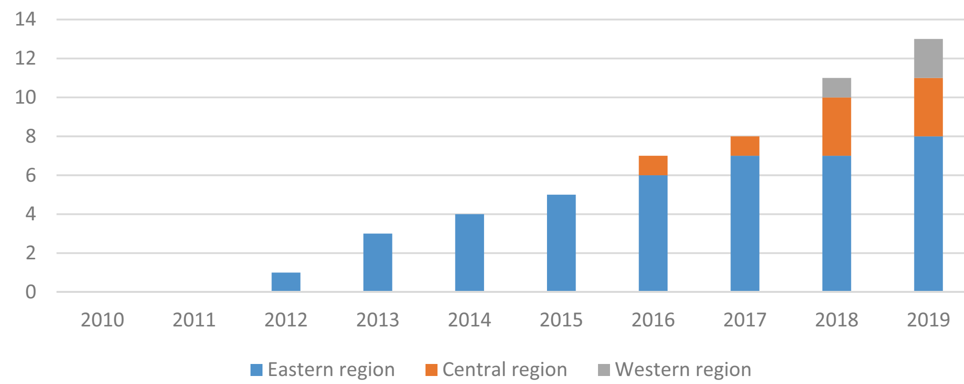


Fig. 5 Threshold level time trend chart for technical accumulation

of innovation still needs to be further improved, and there is still a lot of room for improvement. Under the strategic guidance of "powering the country through innovation," the Chinese government should further accelerate the process of technological innovation and provide a sound development guarantee for the vigorous development of the digital economy. Spatially, there is significant regional heterogeneity in China's technology accumulation level. More than half of the provinces in the high technology accumulation interval are in the eastern region among which Jiangsu, Zhejiang, and Guangdong have been in the high technology accumulation interval. Gathering many scientific and technical personnel, scientific and technological capital and high-tech enterprises are concentrated in these three regions, with significant knowledge spillover effects, profound technology accumulation, and low-carbon driving performance of digital economy; the digital-driven development role of most provinces in the central and western regions is still limited, with only five provinces, including Anhui and Sichuan in the high-tech accumulation interval. Due to the geographical location and economic environment, other provinces and cities in the central and western regions need to strengthen their capacity for technology introduction and independent innovation and improve their level of technology accumulation. Based on the obvious regional heterogeneity of China's technology accumulation, under the strategic guidance of "regional coordinated development," the Chinese government should further encourage high-quality development in the central and western regions. At the same time, the eastern region should give full play to its leading role, and promote the healthy development of the central and western regions by "rich former leads latter, eventually together." In addition, the central and western regions should also focus on cultivating endogenous power, accelerating the transformation of economic development models, and relying on the digital economy to promote high-quality development.

Robustness test

To examine the robustness of the results, we draw on the method of Qi and Li (2018) to adjust the study sample, test the bias of outliers on the results, and verify the robustness of the results. Deleting the sample regions of about 1%, 5%, and 10% of the maximum and minimum digital economy index, we conducted three threshold model tests for 28, 26, and 24 regions in China, respectively. It was found that the impact coefficients and significance levels of the explanatory variables were similar to those tested in the previous study with no significant differences, which indicates the robustness of the empirical results of this paper due to the limitation of text (Table 9 only lists the empirical results of 26 region).

Table 9 Results of model parameter estimation

Parameters	Coef	Std. Err	t	$p>\|t\|$	95% Conf. interval	
City	−1.0053	0.2494	−4.03	0.000	−1.4966	−0.5141
Human	0.0839	0.0197	4.27	0.000	0.0452	0.1226
Open	0.2665	0.0716	3.72	0.000	0.1255	0.4076
Clean	0.0020	0.0020	1.00	0.318	−0.0019	0.0059
DE(TA ≤ 13.1863)	0.0360	0.0423	0.85	0.396	−0.0474	0.1194
DE(13.1863 < TA ≤ 13.2003)	0.0407	0.0862	0.47	0.637	−0.1291	0.2104
DE(TA > 13.2003)	0.1039	0.0423	2.46	0.015	0.0206	0.1872
Cons	0.7224	0.1551	4.66	0.000	0.4169	1.0279

Research findings, policy implications, and future research

Research findings

We have measured the total factor carbon productivity levels in various regions of China, constructed a panel threshold model from the perspective of technology accumulation, and systematically investigated the role of the digital economy on total factor carbon productivity by combining its spatial and temporal heterogeneity factors. The following conclusions are drawn:

(1) The results show that from 2010 to 2019, most provinces in China achieved an increase in total factor carbon productivity, which is consistent with the degree of economic development in various regions of China. In addition, the total factor carbon productivity shows a typical spatial distribution of "high in the east and low in the west." After 2016, the total factor carbon productivity in the eastern region increased significantly, while that in the central and western regions increased slightly. From 2018 to 2019, total factor carbon productivity showed a downward trend to a certain extent, which means that China's low-carbon development is still unstable, insufficient, and incomplete. Promoting carbon emission reduction and high-quality development cannot be "accomplish the whole task at one stroke."
(2) The increase of openness and clean production has a significant positive impact on total factor carbon productivity which can be regarded as the influencing factors to promote China's low-carbon economic growth. In contrast, the driving effect of human capital on total factor carbon productivity is not significant during the sample period, while the increase of urbanization has shown some negative impact on total factor carbon productivity.
(3) On the whole, the development of the digital economy has played a positive role in total factor carbon productivity. It is worth noting that the driving effect is nonlinear under the regulation of technological accumulation. Once the technology accumulation exceeds the critical scale, the positive impact of the digital economy on total factor carbon productivity growth will be enhanced. In contrast, the driving effect of the digital economy on total factor carbon productivity is more limited when the technology accumulation is smaller than the threshold value.
(4) The level of technology accumulation in China's regions is rising continuously, and the number of provinces in the high technology accumulation zone is increasing. Among them, the level of technology accumulation in the country's eastern region is relatively high generally higher with a significant upward trend, while in central and western China, only a few provinces are in the high-tech agglomeration zone, which needs more attention.

Policy implications

(1) Build an inclusive digital economy and increase the digital economy penetration rate. The policy of "raising speed and lowering tariffs" should be implemented to enlarge the number of Internet users, increase the activity of Internet users, and stimulate the effect of the digital economy. At the same time, there is a relatively serious digital divide in China's digital economy. The government should be committed to coordinating regional digital economy development, solving the problem of unbalanced digital economy development between urban and rural areas, increasing digital infrastructure construction and policy support for inland provinces and the rural areas, and providing digital economy services that match regional needs.
(2) Strengthen technological research and development capabilities and raise the level of regional technology accumulation. We should continue to strengthen the technological innovation and independent research and development capacity of domestic enterprises, increase investment in research and development of green production technologies, speed up the transformation of existing scientific research results, promote the role of technological innovation, and improve the country's total factor carbon productivity and the quality of economic development.

Research deficiencies and future research

There are still some deficiencies in this paper, which need to be improved in follow-up research.

(1) In this paper, the panel macroeconomic data of provinces are selected for empirical analysis with limited sample size. In the future, we can try to use microscopic data with a larger sample size for analysis and compare the macro data with the empirical results of the microscope.
(2) This paper only discusses the threshold effect mechanism of technology accumulation. However, it is still worth exploring whether there are other factors that regulate the complex relationship between digital economy and total factor carbon productivity.
(3) This paper only evaluates the digital economy in terms of three relatively critical dimensions: digital infra-

structure, digital industry development, and digital economic environment. However, the digital economy is a broad concept and is not limited to these dimensions. For instance, the aspects such as industrial digitization process and digital government construction may be included, which need to be further studied.

(4) This paper uses the projection pursuit model based on accelerated genetic algorithm to conduct dimensionality reduction evaluation of the digital economy. In the follow-up research, other methods can also be used to calculate the regional digital economy index. At the same time, the spatial distribution, regional differences, and convergence of China's digital economy can be further analyzed by combining spatial correlation and convergence model, so as to improve the research content of the digital economy.

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Declarations

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Consent to participate Not applicable.

Consent for publication Not applicable.

Conflict for publication Not applicable.

Conflict of interest The authors declare no conflict of interest.

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