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Has ICT Contributed to Increased Carbon Productivity in Industry?

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ABSTRACT Enhancing industrial carbon productivity is the key to China's sustainable economic development. Along with the application and development of new-generation network information technologies such as big data, Internet of Things, cloud computing, etc., information communication technology (ICT) has become an essential means to improve national innovation, productivity and strengthen industrial competitiveness, and plays a crucial role in promoting industrial carbon productivity enhancement. Based on China's interprovincial panel data from 2009-2017, this study measured the ICT level through Projection Pursuit improved by an accelerated genetic algorithm and adopted a non-linear threshold regression model to investigate the non-linear impact and its Spatio-temporal heterogeneity of ICT on China's industrial carbon productivity improvement from the perspective of science and technology(S&T) human capital accumulation. The study shows that the overall level of ICT in China is high. There is a digital divide between regions; in general, ICT plays a positive role in enhancing industrial carbon productivity, but there are significant heterogeneous threshold characteristics of science and technology human capital accumulation accumulation. Once the accumulation of science and technology human resource accumulation breaks through the critical scale, the positive effect of ICT on industrial carbon productivity will gradually appear and show a strengthening trend. The temporal and spatial distribution of the threshold for accumulating science and technology human capital accumulation is different.

INDEX TERMS Information and communication technology, industrial carbon productivity, science and technology human resource accumulation, threshold effect, heterogeneity.

I. INTRODUCTION

As the world's second-largest economy, China has received widespread attention for its environmental pollution, especially its carbon emissions [1]. China consumed 4.64 billion tons of standard coal in 2018, an increase of 1.434 billion tons compared to a decade ago, with total carbon emissions of about 10 billion tons, more than the combined carbon emissions of the United States and the European Union, making it the world's largest energy consumer and carbon dioxide emitter [2]. The vast energy consumption has also brought tremendous pressure on China's environmental pollution control, so the Chinese government put forward a strategy to vigorously develop a low-carbon economy in 2007 [2], [3], which involves two major urgent tasks: first, to adjust the mode of economic development and reduce carbon dioxide emissions; second, to ensure the steady economic growth of various industrial sectors. In the context of low-carbon economic development, the only way out for China to achieve the dual goals of reducing carbon emissions and maintaining economic growth is to increase carbon productivity [4].

The Chinese government has always attached great importance to the role of technological progress and structural adjustment in industrial development, especially in response to the trend of the ''Third Industrial Revolution'' [5], the Chinese government in the ''Made in China 2025'' proposed to lead and drive the green development of the manufacturing industry through the application of ICT. The Industrial Green

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Development Plan (2016-2020) released in 2016, further proposed to promote the integration of ICT and green manufacturing, develop mass personalization, network collaborative manufacturing, remote operation, and maintenance services, to reduce resource waste in production and distribution, and promote green lean production methods. Both documents have emphasized the importance of ICT in achieving green development in the industry. It is worth discussing whether the application of ICT in production operations has increased the carbon productivity of Chinese industries. In particular, what is the underlying mechanism linking the two?

Theoretically, there are three main driving paths of ICT to improve industrial carbon productivity: First, the technology spillover effect of the deep integration of ICT and industrial production. The theory of endogenous economic growth attributes the fundamental driving force of economic growth to innovation activities in various fields supported by the accumulation of knowledge in the whole society. The efficiency of information production and dissemination is crucial to the accumulation of knowledge in the whole society. [6], [7] At the same time, the technological advancement brought by ICT has led to the innovation of clean production technology and energy-saving technology and promoted the development of low-carbon production technology and lightweight production methods. [8] Second, the resource allocation effect brought by ICT. The school of social capital theory believes that adequate social capital (such as collaboration, sharing, etc.) contributes to social organizations' efficiency and is one source of economic growth. [9] The mechanism is that since innovation activities have high uncertainty, and capitalists are usually risk-averse, moral hazard and adverse selection caused by information asymmetry will lead to underinvestment in R&D[10] The sharing concept embedded in ICT allows the fragmented supply and demand sides to optimize resource allocation on a public service platform, effectively solving the problem of information silos and thus improving the efficiency of resource allocation[11] Third, the industrial ripple effect of ICT on structural adjustment. In upgrading traditional industries to high-end intelligent industries, the industrial division of labor is deepening in production links and spatially spreading. Reference [12] ICT can effectively weaken corporate boundaries, spawn new service formats, promote high-tech industries and strategic emerging industries, and change the proportional structure between industrial sectors through the integrated development with industries. Through the above three paths, ICT will have a significant impact on industrial carbon productivity.

The advancement of ICT has typical skills-biased characteristics, and the accumulation of S&T human capital accumulation determines the transmission power of the digital economy. Reference [13], [14] The Lucas model shows that economic growth is driven by continuous investment in human capital and physical capital [15]. In economic growth from extensive to intensive, the contribution rate of human capital continues to increase, technological progress has become a key factor, and human capital is the core that determines research and development [16]. Combined with Schumpeter's theory of disruptive innovation and economic growth, this paper argues that the progress of ICT is full of various conflicts and contradictions, including the elimination of old technologies by new technologies, the inability of production equipment and organizational structures established based on old technologies to adapt to the productivity of new technologies [17], the system and mechanism obstacles faced by the development of new business formats, and so on. The typical characteristics of the development and progress of ICT are more knowledge content and faster update speed; therefore, the rapid development of ICT cannot be separated from the sufficient accumulation of S&T human capital accumulation. Simultaneously, considering that there are significant differences in the level of human capital in S&T among regions in China, this paper argues that the impact of ICT applications on industrial low-carbon development may not be purely linear.

In recent years, China has invested a large amount of money and human resources in ICT construction to promote high-quality economic development. However, what is the current level of ICT in China? Is there a digital divide between regions in China? Has the advancement of ICT contributed to the increase in industrial carbon productivity? Is there heterogeneity in the effect of ICT advances on industrial carbon productivity at different levels of technological human capital? We think that these are all questions that need to be considered for further promoting ICT advancement in China. However, no practical explanations for these questions have been provided in existing studies. Due to this situation, for the first time, we have incorporated the heterogeneous threshold of human capital accumulation in S&T into the research framework of ICT-driven industrial carbon productivity improvement, which provides an effective way for regions to explore the power sources and policy design to promote industrial carbon productivity improvement and high-quality economic development.

The possible contributions of this paper are as follows: First, this paper constructs an ICT evaluation index system, improves the projection pursuit model using accelerated genetic algorithms, and scientifically and accurately measures the level of ICT in each region uses the RAGA-PP model. Second, this paper expands the boundaries of ICT for the study of the socio-economic system, overcomes the shortcomings of the unilateral study of ICT and economic growth or environmental protection, and reveals the intrinsic influence of ICT and high-quality development, i.e., industrial carbon productivity. Third, this paper uses a panel threshold model to explore the complex non-linear influence mechanism of ICT on industrial carbon productivity based on the regional heterogeneity of human capital in S&T.

II. LITERATURE REVIEW

Along with the birthing of a new round of industrial revolution, ICT, especially the Internet and big data, cloud computing, and the Internet of Things, display robust convergence characteristics that can improve the efficiency and dematerialization of input factors in production, triggering profound changes in various industries and fields. At the same time, the technological advances embedded in ICT itself not only help eliminate redundancy and waste in the production process but can also synergize with other energy-saving measures of enterprises. Moreover, with the continuous enrichment and improvement of data and research methods at the industry and enterprise, academics are paying great attention to the profit created by ICT in economic growth and examining the impact of ICT on energy saving, emission reduction, and economic growth. The relevant research mainly includes the following parts.

A. THE RELATIONSHIP BETWEEN ICT AND ECONOMIC GROWTH

Lee *et al.* [18] noted that ICT investment has improved economic performance in both developed and Asian NIEs (Singapore, Korea, Taiwan, and Hong Kong) and to a lesser extent in developing countries. The same conclusion comes from Jorgenson and Khuong [19], who examined the impact of ICT investment on global economic recovery from 1989-2003 and found that the growth in ICT investment dominated economic growth in all regions and that this growth effect was more pronounced in advanced economies and emerging Asian economies. Byrne *et al.* [20] decomposed U.S. economic growth from 1974-2012 using a growth accounting framework and found that although the contribution of ICT to U.S. productivity gains from 2004-2012 (40%) was weaker relative to 1995-2004 (50%), it still provided a sustained impetus to U.S. economic growth. ICT is still innovating and advancing rapidly, and the economic impetus provided by the ICT industry cannot be underestimated and is not yet over. Most of the early studies at the national level pointed to an apparent "digital divide" between developing and developed countries regarding the economic effects of ICT. However, with the rapid progress and more widespread adoption of ICT, increased investment in ICT, and improved information infrastructure in developing countries appeared, the economic growth effects of ICT are becoming increasingly evident. Zhou *et al.* believe that ICT has a promoting effect on increasing the potential connection between suppliers and consumers, improving the efficiency of resource allocation and knowledge innovation management. Taking the automotive industry [21] and the healthcare industry [22] as examples, they discussed the importance of ICT technology advancement for developing high-tech industries. They proposed that ICT advancement is a crucial way to promote a high-quality economy in China. Dedrick and Kraemer [23] studied the value of ICT investment in 45 countries and regions based on a series of factors such as human capital, openness to international trade and investment, and telecommunications infrastructure, and found that ICT investment is playing an increasingly important role in productivity growth in developing countries as ICT investment continues to increase and related infrastructure continues to improve. Taking countries along the Belt and Road as the object of study, Iqbal *et al.* [24] proposed that ICT has a significant positive relationship with economic growth. Similarly, taking the five ASEAN countries as an example, Ahmed [25] believes that ICT is one of the essential drivers of total factor productivity. The study by Wei [26] also confirms this conclusion, pointing out that the world's major economies have shifted from a demographic dividend to a digital dividend, the "digital divide" between developing and developed countries is gradually narrowing, and China does not exist or has gotten rid of the "productivity paradox." Based on the analysis of data from 120 cities in China, He *et al.* [27] also agreed that ICT has a significant boosting effect on Chinese firms' productivity.

However, we find that some scholars point out that ICT does not contribute significantly to economic growth. For example, based on OECD country panel data for 1996-2017, Kurniawati [28] pointed out that the sample countries do not promote economic development in ICT infrastructure expansion. Raheem *et al.* [29] empirically analyzed the impact of ICT and financial development on economic development in the G7 countries. The results showed that ICT applications negatively affect economic growth, and ICT development also harms economic development in the long run.

B. THE RELATIONSHIP BETWEEN ICT AND ENERGY SAVING AND EMISSION REDUCTION

With the development of ICT and the increasing research on energy saving and emission reduction, scholars have paid attention to the impact of ICT on energy consumption and carbon emissions. Still, the different research samples and methods make the research findings inconsistent.

Some scholars have found that ICT applications have increased energy consumption and carbon emissions. For example, Gelenbe and Caseau [30] studied the long- and short-term relationship between ICT, carbon dioxide emissions, and economic growth in nine ASEAN countries and found that while ICT development improved economic performance, it also increased regional carbon dioxide emissions. Based on the panel data of E.U. countries from 2001-2014, Park *et al.* [31] found that ICT application has a positive effect on carbon dioxide emissions in the long run. Khan *et al.* [32] introduced a cross term between Internet development and economic development level and between Internet development and financial development. They found that Internet development has a positive effect on carbon emissions. The interaction between ICT and financial development stimulates CO_2 emissions, while the interaction between ICT and GDP reduces pollution. Similarly, through empirical analysis, Moyer and Hughes [33] also proved that ICT could promote carbon emission reduction. However, they believe that relying solely on ICT to reduce carbon emissions has limitations. Only by combining ICT advancement with adjustment of carbon emissions trading prices can the goal of carbon emissions reduction be effectively achieved.

Conversely, empirical studies by some scholars show that ICT promotes regional energy conservation and emission reduction. For example, Wang and Cao [34] used interprovincial panel data from 2000-2015 in China to study the impact of Internet development on energy efficiency and found that Internet development has a positive promotion effect on energy efficiency. Taking Tunisia's panel data from 1975 to 2014 as a research sample, Amri *et al.* [35] analyzed the relationship between ICT, TFP, and carbon dioxide emissions using the breakpoint method. The research results show that ICT is not significantly effective in energy saving and emission reduction. Based on 1990-2015 panel data of 20 emerging economies, Ozcan and Apergis [36], empirically found that ICT application leads to lower air pollution levels. The panel causality test results show a unidirectional causality of ICT on CO_2 emissions. Similarly, using data from a survey of Chinese manufacturing enterprises provided by the World Bank, Zhang *et al.* [5] investigated the impact and mechanism of applying ICT in enterprise production and operation on the energy consumption of enterprises. The research results showed that the application of ICT by enterprises would promote the updating of enterprise technology, machinery, and equipment and improve the flexibility of manufacturing, leading to technological progress and structural optimization, which reduces the energy intensity of enterprises.

Besides, some scholars found that the relationship between ICT application and energy-saving and emission reduction is not linear. For example, Higón *et al.* [37] studied the impact of ICT on carbon emissions in 116 developing countries and 26 developed countries, and the results showed that there is an inverse "U" relationship between ICT development and carbon dioxide emissions. Xie *et al.* [38] used a spatial model to study the impact of Internet technological advancement on environmental quality in China and found that ICT advancement reduced wastewater and sulfur dioxide emissions in China, and there was a spatial spillover effect.

From the above literature analysis, it is easy to find that scholars have conducted a lot of meaningful research on ICT and industrial carbon productivity, which provides a rich theoretical basis for this paper. And, we believe that there still needs more research on it.

First, existing studies have mostly focused on the unilateral development characteristics of ICT to characterize the level of ICT in a region, such as the number of people using cell phones and the number of people employed in the information industry. In this paper, we argue that such a characterization cannot scientifically evaluate the proper level of ICT of a region and may cause bias in the research conclusions. Therefore, we construct an ICT level evaluation index system and use a projection pursuit model based on accelerated genetic algorithms to evaluate the ICT level scientifically.

Second, existing studies mainly focus on the relationship between ICT and economic growth or the impact of ICT on environmental protection. The core of China's high-quality economic development is to achieve a "win-win" situation for both economic development and ecological protection, and we argue that industrial carbon productivity is an essential manifestation of high-quality economic development as it fully integrates both economic output and ecological performance. Therefore, this paper expands the study from examining the relationship between ICT and GDP or environmental pollution to examining the relationship between ICT and industrial carbon productivity, revealing the relationship between ICT and green industrial growth, which has specific guiding significance for China's sustainable economic development.

Third, existing studies have mostly focused on the linear effects of ICT and the economy or the environment, exploring the facilitative or inhibitory effects between the two while ignoring the possible non-linear effects. In this paper, we argue that economic variables contain many non-linear relationships, especially for China, where the regional heterogeneity is very significant, and it is more necessary to analyze its complex influence mechanism. Therefore, this paper fully considers the non-linear threshold effect of human capital accumulation in S&T and introduces it into the complex mechanism of ICT and industrial carbon productivity, revealing how different levels of accumulation affect the role of ICT and industrial carbon productivity and their differences, to test whether ICT effectively promotes industrial carbon productivity growth in China.

III. MODELS AND VARIABLES

A. PROJECTION PURSUIT SETTING BASED ON ACCELERATED GENETIC ALGORITHM

The Projection Pursuit (PP) proposed by Kruscal is a new statistical method to analyze high dimensional data by dimensionality reduction, which can reduce the system's complexity, and its weighting is objective, breaking the limitation of traditional evaluation methods such as Factor Analysis, SFA and DEA. It is an effective method to deal with complex non-normal linear problems [39], which can effectively evaluate multiple indicator samples. Projection Pursuit is an excellent way to perform ICT evaluation, and PP can classify and rank different regions with appropriate gaps in ICT levels. Therefore, based on PP model, the model is constructed as follows.

Step 1: Harmonization of evaluation indicators

For indicators where the bigger the value, the better.

$$x(i,j) = \frac{x^*(i,j) - x_{min}(j)}{x_{max}(j) - x_{min}(j)} \tag{1}$$

For indicators where the smaller the value, the better.

$$x(i,j) = \frac{x_{\max}(j) - x^*(i,j)}{x_{max}(j) - x_{min}(j)} \tag{2}$$

where $\{x*(i,j)\,|\,i = 1,2,\cdots,n; j = 1,2,\cdots,p\}$ is the sample set of evaluation indicator. $x*(i,j)$ is the value of the i sample, n, p are the sample size and the number of indicators, respectively, where $x_{\max}(j)$ and $x_{min}(j)$ represent the maximum and minimum values of the j indicator.

Step 2: Construct projection index function $Q(a)$. The projection pursuit is to transform the p dimensional data $\{x(i,j)\,|j = 1, 2, \cdots, p\}$ in the direction of $a = \{a(1), a(2), a(3), \cdots, a(p)\}$ to the projection value $z(i)$ of one-dimensional projection transformation.

$$z(i) = \sum\nolimits_{j=1}^{p} a(j)x(i,j), (i = 1, 2, \cdots, n) \tag{3}$$

Then it is evaluated according to the one-dimensional scatter diagram $\{z(i)\,|i = 1, 2, \cdots, n\}$, and a in formula (3) is the unit vector. When choosing the projection direction, the projection value's scattering characteristics $z(i)$ should meet the following requirements: the local projection points are as dense as possible. It is better to condense into several clusters, and as a whole, the projection clusters are scattered as much as possible. Therefore, the projection index function can be expressed as:

$$Q(a) = S_Z D_Z \tag{4}$$

where S_Z is the standard deviation of the projection value $z(i)$, and D_Z is the local density of the projection value $z(i)$, namely,

$$S_Z = \sqrt{\frac{\sum_{i=1}^{n} (z(i) - E(z))^2}{n-1}} \tag{5}$$

$$D_Z = \sum\nolimits_{i=1}^{n} \sum\nolimits_{j=1}^{n} (R - r(i,j) \times u(R - r(i,j)) \tag{6}$$

where $E(z)$ is the average value of the sequence $\{z(i)\,|i = 1, 2, \cdots, n\}$ and R is the window radius of the local density. It should be selected so that the average number of projection points in the window is not too small to avoid too large a deviation of the sliding average, and it cannot follow the increase of n and increase too high. R can be determined by experiment. $r(i,j)$ indicates the distance between samples, $r(i,j) = |z(i) - z(j)|$. $u(t)$ is a unit step function, when $t \geq 0$, its function value is 1, and when $t < 0$, its function value is 0.

Step 3: Optimize the projection index function.

When the sample set of each index is given, the projection index function $Q(a)$ only changes with the projection direction change a. Different projection directions reflect different data structure characteristics. The best projection direction is the direction where projection most likely exposes a specific type of feature structure of high-dimensional data. The best projection direction can be estimated by getting the maximum of the projection index function.

Maximize the objective function:

$$maxQ(a) = S_Z \times D_Z \tag{7}$$

The constraint is:

$$\sum\nolimits_{j=1}^{p} a^2(j) = 1 \tag{8}$$

This is a complex non-linear optimization problem that optimizes variables $\{a(j)\,|j = 1, 2, \cdots, p\}$. It is difficult to handle it with traditional optimization methods. Therefore, real-number-encoded accelerated genetic algorithms are used to solve the problem, and the best projection is obtained when the objective function reaches the extreme value.

Step 4: Classification (prioritization)

After substituting the best projection direction a^* obtained in step 3 into equation (3), the projection value $z^*(i)$ of each region can be obtained. Compare $z^*(i)$ with $z^*(j)$, the closer the two are, the more likely the samples i and j are to be in the same category. If $z^*(i)$ is sort from large to small, the samples can be sorted from good to bad.

B. ANALYSIS OF THE ICT INDEX

To test the non-linear threshold heterogeneity effect of ICT on industrial carbon productivity, this paper uses the panel threshold regression method proposed by Hansen [40] to test the relationship between the effect of ICT on industrial carbon productivity under the threshold effect of S&T human capital accumulation.

In this paper, we take industrial carbon productivity as the explained variable, ICT as the explanatory variable, S&T human capital accumulation as the threshold variable, and further introduce a series of control factors such as technological innovation, foreign direct investment, industrial structure and ownership structure to comprehensively investigate the impact of ICT on industrial carbon productivity under the heterogeneous threshold of industrial carbon productivity. Setting a panel threshold model (with a single threshold as an example):

$$\begin{aligned} CPit &= \theta + \alpha_1 ICT_{it} \times I(RDHit \leq \gamma) \\ &\quad + \alpha_2 ICT_{it} \times I(RDHit > \gamma) + \beta_1 TI_{it} + \beta_1 FDI_{it} \\ &\quad + \beta_1 INS_{it} + \beta_1 OS_{it} + u_i + v_t + \varepsilon_{it} \end{aligned} \tag{9}$$

where $I(\bullet)$ is the index function, and γ is the threshold value. u_i is an individual specific effect, v_t is a time-specific effect, and ε_{it} is a random interference item.

Explanatory variables: industrial carbon productivity (CP). In the practice of energy saving and emission reduction, most of the targets set are single factor energy efficiency indexes. For example, the United Nations Convention on Climate Change also gives the responsibility arrangements for emission reduction under the single factor framework. Drawing on the measurement method of Kaya and Yokobori [41], we defined the industrial carbon productivity as the economic benefit per unit of CO_2. Based on the amount of fossil energy consumption in China, including coal, coke, crude oil, gasoline, kerosene, diesel, fuel oil, and natural gas, the carbon emissions for each year are calculated:

$$\begin{aligned} CO_2 &= \sum\nolimits_{i=1}^{8} CO_{2,i} \\ &= \sum\nolimits_{i=1}^{8} E_i \times NVC_i \times CEF_i \times COF_i \times \frac{44}{12} \end{aligned} \tag{10}$$

where E_i is the consumption of fossil fuels, NFC is the low calorific value of fossil fuels, CEF is the carbon content of fossil fuels, and COF is the carbon oxidation factor. This paper calculates the carbon emission factors of fossil fuels based on the "China Industrial Statistical Yearbook" and the

TABLE 1. Carbon emission factors for fossil fuels.

Index	coal	coke	oil	gasoline	diesel	fuel oil	natural gas	kerosene
Carbon emission factors	0.5394	0.8303	0.8363	0.8140	0.8616	0.8823	0.5956	0.8399

carbon content of various fossil energy sources provided by the IPCC (see TABLE 1).

Threshold variable: the accumulation of research and development of human capital (*RDH*). In terms of investment in S&T innovation, scholars chose human and financial resources indicators to quantify. But the fundamental innovation talents of S&T are the foundation and main driving force of innovation. The internationally standard index is the full-time equivalent of R&D personnel, which can more accurately measure the amount of S&T human capital investment than the index of R&D personnel. Therefore, to explore the heterogeneous impact of different S&T human capital bases on the growth of carbon productivity in ICT-driven industries, this paper draws on the measurement method of Xiao and Fan [42] and uses R&D personnel full-time equivalent as the characterization variable of S&T human capital accumulation.

Core explanatory variable: information and communication technology (ICT). Concerning the measurement of ICT level, as no comprehensive index on informatization has been officially disclosed yet, the measurement faces specific difficulties and challenges, leading most scholars to use single indicators such as the number of employees in the I.T. service industry or the penetration rate of Internet users instead. The application of ICT is a systematic project, and the indicators of a particular aspect can only reflect the partial facts of ICT development. Still, they cannot objectively reveal their fundamental level [43]. Based on the actual situation of China's informatization development, this paper constructs a comprehensive development level measurement system for China's interprovincial ICT from the four dimensions of information industry infrastructure construction, ICT penetration rate, ICT business application and ICT development environment, and insists on the five aspects of comprehensiveness, scientificity, orientation, effectiveness, and operability to screen the corresponding subdivision indicators. The index system and panel data were used to calculate an integrated level of interprovincial ICT adoption index using projection pursuit based on an accelerated genetic algorithm.

Control variables: A series of controls for the effects of industrial carbon productivity growth, taking into account existing studies.

Industrial Structure (INS). Measured using the ratio of the value-added of the secondary industry to the value-added of the tertiary industry.

Ownership Structure (O.S.). Measured using the ratio of private-sector employment to total regional employment.

Foreign Direct Investment (FDI). Measured using the ratio of foreign direct investment (FDI) to GDP.

Technological Innovation (T.I.). Compared to indicators such as revenue from new product sales or patent grants, the number of patent applications is less affected by external influences, which directly reflects the technological innovation capacity of the region. Besides, technological innovation is a process of continuous accumulation. The early technological innovation base has an essential impact on the current industry's carbon productivity; i.e., technological innovation is a stock concept. Therefore, this paper refers to the approach of Han *et al.* [4] and uses the perpetual inventory method to inventory the number of patent applications to characterize the level of technological innovation in the region. The approach is as follows:

$$TI_{it} = (1-\delta)TI_{t-1} + PAT_{t-1} \tag{11}$$

where TI_{it} is the stock of technological innovation capacity at the beginning of period t. PAT_{t-1} is the number of patents granted in this period. δ is the depreciation rate.

It can be seen that to require TI_{it}, two key issues must be solved: First. Determine the depreciation rate δ. It is a constant. In the previous research, scholars often set a value of 10%; second, find the initial stock TI_0. In the perpetual inventory model, the stock of technological innovation capabilities at the beginning of the period is generally calculated as follows:

$$TI_0 = \frac{PAT_0}{\bar{g}+\delta} \tag{12}$$

where TI_0 is the stock of technological innovation capabilities in the first year, PAT_0 is the number of patent applications in the first year, and $\bar{g}$ is the average annual logarithmic growth rate of the number of patents granted during the data acquisition period.

C. DATA SOURCES AND PROCESSING

In this paper, 30 regions in mainland China (Tibet was missing a lot of data and was not included in the sample) from 2009-2017 were selected as the study sample. The raw data are obtained from the China Statistical Yearbook, China Energy Statistical Yearbook, China Environmental Statistical Yearbook, China Internet Development Status Statistical Report, and provincial and municipal statistical yearbooks. The monetary quantities were deflated accordingly considering the influence of prices, and all of them are based on the base period of 2009. TABLE 2 shows the correlation matrix and summary statistics for the variables.

IV. EMPIRICAL ANALYSIS

A. LEVEL OF ICT APPLICATION IN CHINA

In general, the level of ICT in China is high, with an average value of 1.06 (shown by the dotted line in Figure 1). However, the digital divide still exists due to differences in economic development, Internet infrastructure construction, education level, and people's perceptions and thinking. The correlation between the level of ICT and the speed of economic development in each region is high. The top-ranked

TABLE 2. Correlation matrix and summary statistics of variables.

Variables	*CP*	*ICT*	*RDH*	*FDI*	*INS*	*OS*	*TI*
CP	1.000						
ICT	0.6045***	1.000					
RDH	0.3749***	0.7677***	1.000				
FDI	0.5449***	0.3888***	0.2157***	1.000			
INS	-0.5161***	-0.2064**	0.1878**	-0.4302***	1.000		
OS	0.7001***	0.5062***	0.3015***	0.7790***	-0.4287***	1.000	
TI	0.5431***	0.8828***	0.9024***	0.2960***	-0.0893	0.4048***	1.000
Sample size	270	270	270	270	270	270	270
Average value	0.498	0.821	10.473	0.103	0.460	0.196	11.592
Standard deviation	0.416	0.296	1.334	0.178	0.083	0.153	1.541
Minimum value	0.054	0.049	6.426	0.008	0.190	0.024	7.424
Maximum value	3.636	1.580	13.033	1.102	0.590	0.936	15.054

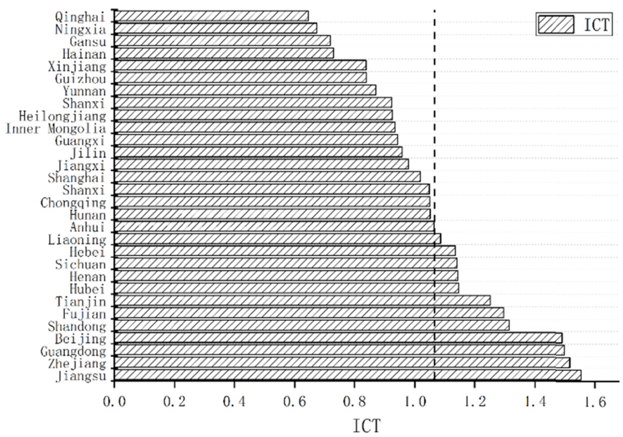

FIGURE 1. ICT technology level in China.

provinces in terms of penetration rate are mainly concentrated in the eastern region, with the ICT level index of Jiangsu, Zhejiang, Guangdong, and Beijing all higher than 1.4, significantly higher than other provinces. In contrast, the western and northeastern regions are relatively backward, especially Qinghai and Ningxia provinces. As the western and northeastern regions have fewer high-technology and knowledge-intensive industries, and because of geographic location, capital, and economic environment, there is an urgent need to raise ICT.

TABLE 3. Results of the threshold effect test.

Threshold	F-value	P-value	No. of B.S.	Threshold value		
				10%	5%	1%
single threshold	64.09**	0.0433	300	40.8281	56.2034	126.659
double threshold	64.28**	0.0433	300	39.2237	54.6056	107.6916
triple threshold	63.31*	0.0600	3Ï00	40.0181	74.6572	124.6361

TABLE 4. Estimated results of the threshold.

Threshold	Threshold estimates	95% confidence interval
single threshold	10.7754	[10.7749, 10.8016]
double threshold	10.8602	[10.8493, 10.8727]
triple threshold	10.8727	[10.8602, 10.8876]

B. HETEROGENEOUS THRESHOLD EFFECTS

Firstly, the accumulation of human capital in S&T is used as the threshold variable to test different threshold conditions. From Table 3 and Table 4, the single threshold and double threshold are significant at the 5%, and the triple threshold is significant at the 10%, with an F value of 63.31 and a self-sampling P-value of 0.06. Based on Hansen's threshold theory, the model has a triple threshold effect on accumulating S&T human capital accumulation, with the thresholds of 10.7754, 10.8602, and 10.8727, respectively (see Table 4).

Secondly, with likelihood ratio function plots, we show the estimation results and the corresponding 95% confidence interval construction of the thresholds of human capital accumulation in S&T. In Figure 2, when the thresholds are 10.7754, 10.8602, and 10.8727, respectively, the Likelihood Ratio Statistical Test (L.R.) is zero. The corresponding 95% confidence intervals are within the acceptance of the model's original assumptions $H_0 : \gamma = \gamma_0$ And the threshold estimate is equal to its actual value. Thus, based on the threshold heterogeneity interval, it could be divided into S&T human capital accumulation ($RDH \leq 10.7754$), medium S&T human capital accumulation ($10.7754 < RDH \leq 10.8602$), and relative high accumulation of S&T human capital ($10.8602 < RDH \leq 10.8727$) and high S&T human capital accumulation ($RDH > 10.8727$).

The results of the panel threshold regressions are shown in Table 5. For the control variables, a 1% increase in technological innovation, foreign direct investment, and ownership structure will increase industrial carbon productivity by 0.0506%, 0.4223%, and 0.3802%, respectively. Firstly, technological innovation is an essential source of technology accumulation in the region, especially for environmental

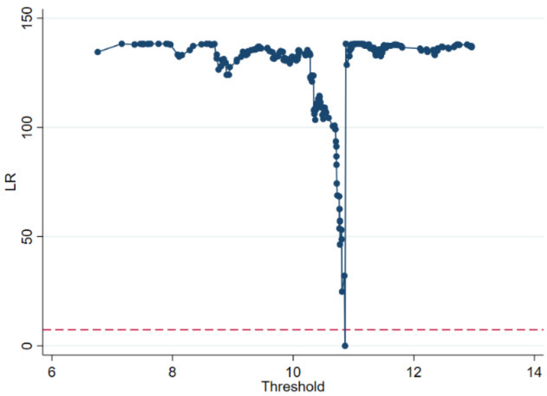

FIGURE 2. Single threshold and confidence intervals.

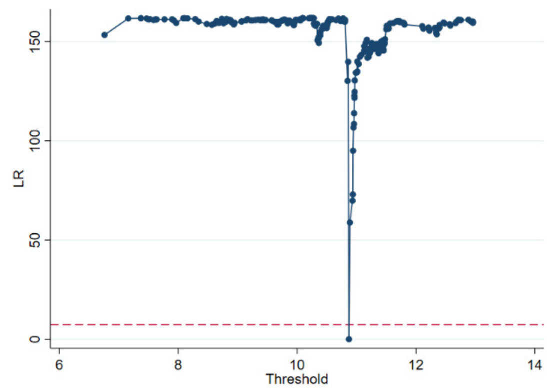

FIGURE 3. Double threshold and confidence intervals.

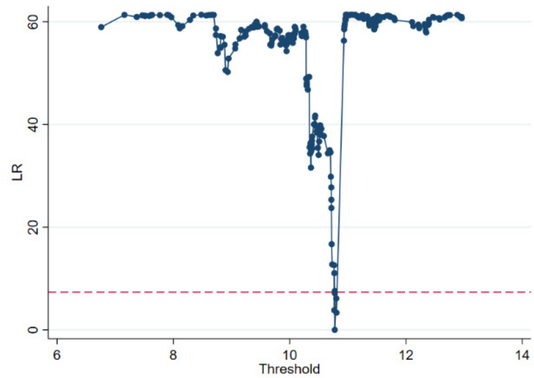

FIGURE 4. Triple threshold and confidence intervals.

TABLE 5. Results of model parameter estimation.

Parameters	Coef.	Std. Err	t	$p > \|t\|$	95% Conf. Interval	
TI	0.0506	0.0248	2.04	0.042	0.0018	0.0995
FDI	0.4223	0.1240	3.41	0.001	0.1780	0.6665
INS	0.1169	0.2797	0.42	0.676	-0.4342	0.6680
OS	1.3802	0.1371	10.07	0.000	1.1102	1.6502
ICT ($RDH \leq 10.7754$)	0.1260	0.0860	1.47	0.144	-0.0434	0.2954
ICT ($10.7754 \leq RDH < 10.8602$)	0.3344	0.0939	3.56	0.000	0.1495	0.5194
ICT ($10.8602 \leq RDH < 10.8727$)	0.3422	0.1699	2.01	0.045	0.0075	0.6769
ICT ($RDH > 10.8727$)	0.3437	0.0851	4.04	0.000	0.1761	0.5114
cons	-0.6602	0.3260	-2.02	0.044	-1.3026	-0.0178

technologies that aim at energy conservation and emission reduction. The risk of environmental pollution faced by the region is ever-changing, which requires enterprises to adapt to the changing situation and continuously increase the pace of technological innovation to promote the improvement of carbon productivity in the industrial sector. Secondly, foreign direct investment is an intuitive manifestation of the introduction of foreign investment and opening up, which indicates that China's accelerated development of international trade has produced significant technological spillover effects that are conducive to the enhancement of China's industrial carbon productivity. Thirdly, ownership is the basis for the role of the market mechanism. The increase in the degree of marketization indicates that administrative plans are being reduced or withdrawn. When the market allocates economic and environmental resources more, it is more conducive to economic development and the improvement of ecological efficiency, and thus enhance industrial carbon productivity. Finally, the positive effect of industrial structure on industrial carbon productivity is not significant, and China's industrial restructuring has not played a substantial role in enhancing industrial carbon productivity. This shows that China's industrial structure adjustment should not only improve the quality of traditional industries and gradually reduce the proportion of sunset industries with backward technology and low economic efficiency, but also focus on increasing the proportion of high-tech industries in the industrial structure to improve the utilization and allocation efficiency of resource elements and reduce environmental pollution and greenhouse gas emissions, which also means that future industrial carbon productivity enhancement needs breakthroughs in industrial restructuring.

There is a significant triple threshold effect of ICT on the carbon productivity of the industry, which is the accumulation of S&T human capital. On the whole, ICT plays a beneficial promoting effect on industrial carbon productivity. As the level of S&T human capital accumulation strengthens, the promotion effect becomes more apparent. When the level of S&T human capital accumulation is below the threshold value of 10.7754, the promotion effect of ICT on industrial carbon productivity is weak and insignificant. When the level of S&T human capital accumulation is higher than 10.7754, the impact of ICT on industrial carbon productivity plays a significant positive effect, showing a significant positive correlation at the 1% level. Along with the increasing level of S&T human capital accumulation, the promoting effect of ICT on industrial carbon productivity is increasing. The promoting effect of ICT on industrial carbon productivity is most pronounced when the level of S&T human capital accumulation crosses the triple threshold of 10.8727. Each 1% increase in ICT will drive *C.P.* correspondingly an increase of 0.3437%. This indicates that the promotion effect of ICT-driven carbon productivity improvement is constrained by the level of S&T human capital accumulation. The driving effect of ICT is not significant at lower levels of S&T human capital accumulation. In comparison, *ICT* plays a beneficial driving effect at higher levels of S&T human capital accumulation. As the regional stock of S&T human capital accumulation becomes larger and larger, once the critical size is exceeded, the positive driving effect of ICT tends to increase.

Thus, this paper argues that ICT, as a skill-biased technological advancement, requires a higher workforce quality level. The complementarity and synergy of S&T human capital accumulation mainly affect the realization of ICT's low-carbon effect.

When the accumulation of S&T human capital is low, ICT cannot effectively promote industrial carbon productivity and decouple economic growth from environmental management. The possible reasons are: China's ICT industry started late, the development speed is rapid, and the scale is increasing, while the accumulation of S&T human capital matching the industrial development has not yet been formed, and the problem of supply of high-quality talents falling short of demand is more prominent, resulting in the ineffective application of ICT. At the same time, the development of the ICT industry is a system project that requires a large investment in scientific research funds and infrastructure construction, which, to a certain extent, will bring negative environmental externalities. But due to insufficient accumulation of S&T human capital, it cannot offset the negative environmental externalities and thus cannot enhance the carbon productivity of the industry.

The network spillover effect of ICT is more pronounced in regions with a high stock of accumulated S&T human capital. Firstly, as S&T human resources are mainly concentrated in high-tech industries such as electronics and communications, the agglomeration effect is remarkable; and there is specific tacit knowledge in S&T human capital accumulation, which can be promoted by ICT through "learning by doing," thus enhancing the production efficiency of industries. Secondly, based on the advancement of information and communication technologies such as computers and the Internet, S&T human capital can acquire new knowledge, new technologies, and new information at the lowest cost, process and utilize the information of technological advancement, and further develop itself on the original technological level, which can effectively promote industrial technology upgrading and business process innovation, and adjust and form the optimal organizational structure to adapt to the flow of information. These corresponding organizational changes also have a skill-biased character, contributing to the progress of economic intensification and enhancing the carbon productivity of industries. Third, S&T human capital accumulation is an essential source of knowledge accumulation and scientific and technological innovation; the knowledge, skills, and creativity possessed by S&T human capital accumulation are the necessary supporting conditions for the application of ICT; the effective integration of ICT and S&T human capital accumulation is the primary condition for the application of ICT; the accumulation of S&T human capital can promote the application of high-end technologies such as the Internet of Things and big data, and promote the participation of the digital economy. The market economy operates, which promotes the transformation and upgrading of traditional industries to high-end manufacturing and the improvement of industrial carbon productivity.

TABLE 6. **Spatial distribution of threshold levels for S&T human capital accumulation (2009 and 2017).**

	$RDH \leq 10.7754$	$RDH > 10.7754$
2009	Beijing, Tianjin, Hebei, Shanxi, Inner Mongolia, Liaoning, Jilin, Heilongjiang, Anhui, Fujian, Jiangxi, Hubei, Hunan, Guangxi, Hainan, Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang	Shanghai, Jiangsu, Zhejiang, Shandong, Henan, Guangdong
2017	Shanxi, Inner Mongolia, Jilin, Heilongjiang, Jiangxi, Guangxi, Hainan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang, etc.	Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Anhui, Fujian, Shandong, Henan, Hubei, Hunan, Guangdong, Chongqing, Sichuan, etc.

C. SPATIO-TEMPORAL HETEROGENEITY

From the spatial distribution of S&T human capital accumulation threshold levels in Table 6, most Chinese provinces were at the low S&T human capital accumulation level in 2009 ($RDH \leq 10.7754$). Only six provinces (Shanghai, Jiangsu, Zhejiang, Shandong, Henan, and Guangdong) have high levels of S&T human capital accumulation ($RDH > 10.7754$), accounting for 20% of the total; most of the central west and northeastern regions are still the low S&T human capital accumulation areas, due to their poor technical and economic environment, and high-tech industries are fewer. Through the development of the digital economy brought about by industrial carbon, productivity enhancement is not significant. With the increasing number of provinces crossing the threshold of S&T human capital accumulation, by 2017, the eastern coast and central provinces are basically out of the low S&T human capital accumulation regions. For the high S&T human capital accumulation provinces, their knowledge accumulation, industrial ecological concepts, and government support system are perfect, and the application of ICT helps to enhance industrial carbon productivity significantly.

V. RESEARCH FINDINGS AND IMPLICATIONS

A. RESEARCH FINDINGS

Based on the measurement of the level of ICT application in different regions of China, this paper first constructs a nonlinear panel threshold model from the perspective of S&T human capital accumulation and systematically investigates the effect of ICT on industrial carbon productivity by taking into account its spatial and temporal heterogeneity factors, and draws the following conclusions.

(1) The level of ICT application in China is high, but there is an apparent digital divide between regions. The level of ICT application is high in the eastern part of the country but low in the western and northeastern parts of the country, which need improvement.

(2) The impact of technological innovation, foreign direct investment, and ownership structure on industrial carbon productivity is significantly positive, which is an essential means to promote China's economy. In contrast, the low-carbon development effect of industrial structure is not significant in the sample period.

(3) On the whole, ICT has a positive effect on industrial carbon productivity. Still, its driving effect is limited by the impact of S&T human capital accumulation, and the threshold of heterogeneity is remarkable. Once the accumulation of S&T human capital breaks through the critical scale, the positive effect of ICT on the growth of industrial carbon productivity will be enhanced. Therefore, the low-carbon effect of ICT is not significant in areas with low levels of S&T human capital accumulation.

(4) The heterogeneity in the accumulation of human capital in S&T in regions where the carbon productivity of ICT-driven industries increases is remarkable, with large differences in spatial and temporal distribution. The number of regions with low S&T human capital accumulation is decreasing. In contrast, the level of high S&T human capital accumulation areas shows an increasing trend, and a few provinces in the western and northeastern regions are still in low S&T human capital accumulation, requiring special attention.

B. IMPLICATIONS

At present, the new round of industrial revolution led by ICT has formed a historic convergence with China's economy entering a new normal and the successful transformation of the old and new dynamics of economic development. China must firmly grasp the significant opportunities brought about by the new round of scientific and technological revolution and industrial transformation led by a new generation of ICT, rely on ICT to achieve incremental expansion driven by factor input growth to rely on factor quality enhancement and innovation-driven quality growth transformation, to tap new industrial and economic growth points, to provide a robust power guarantee for the improvement of the quality of economic growth, which is very important for the development of China's economy. At present, it is of great strategic significance for China to achieve sustained and efficient economical operation on a medium- to the high-speed platform and to comprehensively improve the quality and efficiency of economic growth. The specific policy implications are as follows.

(1) Promoting the advancement and application of ICT. The government can increase its support for the informatization construction of manufacturing enterprises by setting up enterprise informatization support funds. In particular, in the field of industrial energy conservation and emission reduction, special funds should be arranged to encourage enterprises to use ICT to reform traditional production equipment and processes, which will not only help enterprises to progress in production technology and management innovation but also promote enterprises to "clean production" and green manufacturing.

(2) Accelerating the "integration of informatization and industrialization" strategy and enhancing the penetration and radiation effect of the ICT industry. The transformation and upgrading of traditional industries by ICT are gradually extending from the tertiary industry to the secondary and primary industries. The implementation of strategic actions such as "Internet +," "Made in China 2025", "Mass Entrepreneurship, and Mass Innovation" has enabled the development of a new generation of ICT and the manufacturing industry more closely integrated and promoted the intelligent, digital and service-oriented manufacturing industry and green development. In the specific promotion, the experience and mature technology of "typical enterprises" should be summed up and then gradually radiated to many small and medium-sized industrial enterprises to reduce the cost and risk of strategy implementation.

(3) Paying attention to the integration of industrial chain by ICT and encouraging backbone enterprises to explore the use of ICT to establish a comprehensive energy recycling system, such as guiding large enterprises in the industry to use the Internet of Things technology to integrate upstream and downstream enterprises in the industrial chain, to facilitate the transformation of the production value chain of Chinese enterprises into an ecological industrial chain.

(4) Promoting the accumulation of S& T human capital virtually in all regions. For the western region, in particular, local governments should strengthen investment in human capital, raise the level of public education expenditure, expand the access of social resources to the education sector, and encourage and guide social forces to establish education, thus fundamentally enhancing the level of S&T human capital.

There are still some shortcomings in this paper that need to be improved. First, we use 30 regions in China as research samples to explore the phased role of human capital in S&T between ICT and carbon productivity. The conclusions obtained are also based on data from China. Whether it is universal, whether it applies to countries with other economies is still unknown. For example, it may not apply to developed countries with a high level of development of the information industry and sufficient human capital accumulation. Future research should select countries with different economic scales as the research objects to draw more comprehensive research conclusions. Second, this paper has not further explored whether other factors make the threshold effect between ICT and industrial carbon productivity, and other threshold variables may be omitted. Third, due to data availability limitation in this paper, the sample period in this article is from 2009 to 2017, and the data sample is not sufficient. The analysis results cannot fully reflect the relationship between ICT and industrial carbon productivity. Future studies should further experiment with panel data at the city level or microdata at the enterprise level to examine the driving effect of ICT on industrial carbon productivity in more detail.

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