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The Digital Economy and Carbon Productivity: Evidence at China's City Level

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Abstract: Based on the panel data of 285 prefecture-level cities in China, this paper empirically tests the impact of digital economic development on carbon productivity by using a two-way fixed effect model, intermediary mechanism model and threshold mechanism model. The results show that: (1) the digital economy can significantly improve carbon productivity, and this conclusion is still valid after a series of robustness tests. (2) An intermediary mechanism test found that technological innovation, reducing energy consumption intensity and improving urban productivity are the three primary paths through which the digital economy significantly improves carbon productivity. (3) A threshold mechanism test found that the promotion effect of the digital economy on carbon productivity is also affected by the degree of marketization and the level of human capital, showing a single threshold effect and a U-shaped trend. (4) The impact of the digital economy on carbon productivity has regional heterogeneity, urban agglomeration heterogeneity, and resource-based city heterogeneity. This study provides substantial empirical evidence for the relevant authorities to formulate green development policies from the perspective of digital economy development.

Keywords: digital economy; carbon productivity; marketization; human capital

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1. Introduction

The global climate problem caused by the continuous increase in greenhouse gas emissions is becoming increasingly severe, and all sectors of the world are encouraging the promotion of low-carbon development [1]. In the face of this challenge, China has proposed the strategic goals of achieving carbon peaking by 2030 and carbon neutrality by 2060, which fully express China's determination to mitigate climate change and enhance carbon productivity [2]. At present, scholars have mainly investigated the influence of various factors on low-carbon development in the traditional economy [3], technological progress [4], foreign direct investment [5], and government industrial planning [6]. There are still significant gaps in the research on low-carbon development in new economic forms, especially the impact of digital economy on carbon productivity. The "14th Five-Year Plan for Digital Economy Development", announced by the State Council on 12 January 2022, points out that by 2025, the value added of core industries in the digital economy will increase to 10% of GDP, and the penetration rate of industrial Internet platforms will increase to 45%, among other strategic goals. The digital economy is not only a new industry, but also has a significant role in promoting traditional industries. It can use advanced information technology as the basis to promote technological innovation, structural upgrading and paradigm shift and provide an essential engine for cultivating new dynamics of economic growth. Moreover, embedding the digital economy in key carbon emissions areas such as transportation, buildings, energy, and electricity points the way to comprehensive low-carbon development and green transformation [7]. So, can the digital economy effectively boost carbon productivity? If so, what are the pathways and mechanisms by which this impact occurs? Is there regional heterogeneity between regions? A review of existing studies reveals that scholars mainly study the relationship between the digital economy and carbon emissions [8], the impact of digital technologies on green development [9], and the impact of Internet development on energy efficiency and carbon performance [10]. Moyer and Hughes [11] found that information network dissemination can reduce carbon emissions through three paths: increased production efficiency, reduced energy intensity, and renewable energy costs. Shabani and Shahnazi [12] proved that the development of Internet technology helps to reduce environmental pollution and promote green development from the perspectives of public participation, the environmental intelligence industry and government environmental regulation. Zhang et al. [13] argued that the digital economy affects carbon performance mainly through three mediating mechanisms: energy intensity, energy consumption scale, and urban greening. Bai and Sun [14] examined the intrinsic mechanisms and effects of the development of the digital economy on carbon productivity in terms of cost, demand, and innovation. Liang et al. [15] argue that the digital economy can replace or transform the traditional economy with high costs, pollution, and emissions, thus enhancing carbon productivity. Han et al. [16] pointed out that the digital economy can increase carbon productivity by enhancing the level of technology accumulation. However, the existing literature directly investigates the impact of the digital economy on carbon productivity is relatively small, the theoretical discussion and empirical tests need to be improved urgently, and the studies have not reached consistent conclusions. Therefore, the marginal contribution of this study lies in the following aspects. First, we measure the digital economy and carbon productivity at the city level and empirically test the positive effect of the digital economy on carbon productivity by using the panel data of 285 prefecture-level cities from 2011 to 2019. Second, we explore the mechanism of the digital economy affecting urban carbon productivity from three aspects, technological innovation level, energy consumption intensity, and urban production efficiency, and clarify the mechanism and paths involved. Third, this paper incorporates the degree of marketization and the level of human capital into the analytical framework to investigate their threshold effects on the impact of the digital economy on carbon productivity.

2. Mechanism Analysis and Research Hypothesis

2.1. Digital Economy and Carbon Productivity

As a new economic form, the digital economy has the advantages of being green, innovative and sharing, which can enhance urban carbon productivity through infrastructure, resource allocation, and structural optimization.

Infrastructure dimension of the digital economy. First, the digital economy can implement sustainable development goals through digital infrastructure, based on facilities such as 5G Internet, cloud computing and intelligent devices combined with urban production factors to support government policies to promote low-carbon urban development. Secondly, the new infrastructure formed by transforming and upgrading traditional facilities with the help of digital technology can also contribute to green and low-carbon development. For example, based on digital information technology, intelligent manufacturing workshops can predict and control carbon emissions [17], and building a carbon trading platform can reduce carbon intensity and enhance carbon productivity [18]. Finally, enhanced investment in digital infrastructures such as smart campuses, smart hospitals, innovative energy infrastructure development, and intelligent transportation infrastructure can effectively enhance carbon productivity [19].

Resource allocation dimension of the digital economy. Based on digital information mining of market demand and consumer preferences, the digital economy can match supply and demand and re-match resource factors such as capital and labor to improve resource allocation efficiency, which is an essential factor affecting carbon productivity. On the one hand, enterprise producers can use cutting-edge digital technologies such as artificial intelligence, virtual reality and the Internet of Things to analyze and plan the reorganization of product data and resource data to re-invent production processes, improve enterprise productivity and resource utilization efficiency, and avoid resource waste and thus achieve energy conservation and emission reduction [20,21]. On the other hand, the digital economy can transform the quality of traditional factors of production, such as labor, capital and technology, by bringing into play the substitution effect of data factors, bringing about a multiplier effect, as well as replacing traditional factors of production and reducing the use of highly polluting and energy-consuming resources [22].

The structural optimization dimension of the digital economy. The digital economy mainly exerts structural optimization effects through technology penetration and industrial convergence, with biased technological progress and improvements in energy structures enabling the transfer of production factors from inefficient to efficient sectors, ultimately enhancing carbon productivity [23]. The digital economy can improve the operational efficiency of industrial organizations and optimize the industrial structure through the competitive effect and scale effect [24]. In the process of industrial structure upgrading, carbon productivity can be improved by reducing highly polluting and energy-consuming industries and improving the generation of energy structures.

At the same time, the digital economy can also influence carbon productivity in three ways.

Technological innovation. First, technological innovation by enterprises is characterized by high adjustment costs, uncertainty of results, and excessive inputs. The digital economy enables efficient, low-cost, and low-energy technological innovation, creating conditions for the technological development of low-carbon technology enterprises and related industries [25]. Second, the digital economy, with its characteristics of sharing, permeability and spillover, will change the ratio and types of production input factors and reconfigure the way resources are allocated [26,27], and enhance regional technological innovation efficiency by breaking administrative and market monopolies and promoting rational allocation of R&D resources. In addition, the digital economy can promote interconnection, knowledge sharing, and innovation collaboration among innovation agents to achieve an enhanced level of technological innovation [28]. The enhancement of technological innovation can improve the efficiency of fossil energy use and reduce carbon emissions while also alleviating the problems of electricity consumption and insufficient storage of new energy [29]. Finally, collating and analyzing information such as green products and consumer preferences through digital technology can lead manufacturers and enterprises to increase market demand for green technologies and promote the formation of high-tech industries, thus increasing carbon productivity [30].

Energy consumption intensity. First, the application of the digital economy in socioeconomic activities such as production and operation, transportation and travel, and government decision making can directly or indirectly reduce energy consumption intensity and thus improve carbon productivity [31]. Second, an analysis of ICT investments in Japan and Korea shows that enhanced ICT investments can reduce labor and energy losses [32]. Analysis of data from EU countries shows that the development of the digital economy can promote the "virtualization" and "dematerialization" of economic activities, thereby reducing the intensity of traditional energy consumption and increasing carbon productivity [33]. A study of environmental issues in China found that the digital economy can significantly reduce coal-based energy consumption. However, this effect is only significant in non-resource-based and western provinces [34]. As the trend of energy structure changes differently from province to province, it can lead to a "high" or "low" carbon situation in each region [35]. Finally, Zhang et al. [13] suggest that the digital economy, with its accelerated factor flows, can reduce energy consumption intensity and improve the energy consumption structure, ultimately increasing urban carbon productivity.

Urban production efficiency. First, the digital economy enhances urban production efficiency by improving the efficiency of producers' capital financing, enhancing enterprises' production efficiency, expanding consumers' consumption space, and broadening consumers' income paths [36]. Secondly, the digital economy can break spatial constraints, allocate scarce resources across regions, deepen industrial and economic ties, and strengthen the spatial agglomeration of urban economies, thereby improving urban productivity [37]. In addition, the transformation of the industrial structure to high-end services will catalyze urban productivity, and the digital economy contributes to the upgrading of the industrial structure, which can improve urban productivity through the rational allocation of factor resources [38]. Finally, the digital economy can help establish digital government and improve the efficiency of urban operations. The government simplifies governmental procedures through digital technology, saves social resources, improves the efficiency of business processing, stimulates urban vitality, and the digital government can stimulate the inherent potential of the digital economy [39], which facilitates the market playing a maximizing role in economic development and improves carbon productivity.

In summary, the digital economy will affect the carbon productivity of Chinese cities in three ways: technological innovation, energy consumption intensity, and urban production efficiency. Therefore, the following Hypothesis 1 is proposed.

Hypothesis 1 (H1). *Digital economy development can increase carbon productivity.*

2.2. Digital Economy, Marketization and Carbon Productivity

With the deepening of market-oriented reforms, resource allocation is gradually changing to a market-oriented method [40]. Reducing market segmentation can alleviate the imbalance of development between regions and can promote market integration by reducing transaction costs, technology costs, and logistics costs of economic activities [41]. A higher marketization level means less government administrative intervention, and excessive government intervention will cause industrial agglomeration to not reflect the scale effect and become less attractive to potential entrants [42], and will lead to distorted factor prices that do not genuinely reflect the supply and demand in factor markets. The improvement of marketization level can help break the barriers to entry and exit of the digital economy, allocate resources more efficiently and rationally, and enable industries to generate economies of scale and increase productivity [43]. At the same time, market competition is also formed when market integration occurs. Fierce market competition can force innovation agents to make high-quality innovations [44], thus increasing carbon productivity. In addition, as the demand for carbon emission market gradually increases, carbon emission rights trading shows a rapid development trend, and carbon financial derivatives such as carbon options, carbon bonds and carbon forwards are also emerging. However, China's carbon trading market still has problems such as small scale, few participating parties and inadequate laws, so it is necessary to build a more open and market-oriented carbon trading market to reduce carbon emissions and improve carbon productivity. Accordingly, Hypothesis 2 is proposed.

Hypothesis 2 (H2). *The higher the level of marketization, the stronger the positive effect of the digital economy on carbon productivity.*

2.3. Digital Economy, Human Capital and Carbon Productivity

As a new economic form, digital economy is gradually changing the traditional way of living and working, requiring corresponding digital competencies to adapt to digital life, which puts new demands on human capital [45]. Korshunova [46] and Tuguskina et al. [47] point out that possessing an intellectual, high level of human capital is an important driver and the primary resource for developing the digital economy. Zhong et al. [48], Yang and Cai [49] demonstrate that human capital positively contributes to the digital economy affecting carbon productivity. The level of human capital as a critical factor affecting carbon emissions has become a consensus among academics [50]. Most studies have concluded that human capital improves carbon productivity by reducing energy consumption mainly through improving the efficiency of technological innovation [51] and energy use efficiency [52]. Jin et al. [53] found in a dynamic study that human capital can reduce pollution and increase carbon productivity only in the long run. Human capital is an essential source of knowledge accumulation and technological innovation; different accumulation levels generate different technological spillover effects, learning ability and innovation potential, which determines a significant threshold effect of human capital level [54]. Therefore, to fully unlock the dividends of the digital economy, a new type of human capital needs to be cultivated. Accordingly, Hypothesis 3 is proposed.

Hypothesis 3 (H3). *The higher the level of human capital, the stronger the positive effect of the digital economy on carbon productivity.*

3. Methodology and Data

In previous studies, few scholars have conducted systematic and in-depth theoretical and quantitative research on the digital economy and carbon productivity. However, in the context of China's green economic development, an in-depth study of the relationship between the two has become necessary. This paper discusses the impact of the digital economy on carbon productivity, which is a causal identification test. There are five classical econometric models for causal identification tests: OLS, regression discontinuity design, difference-in-difference, instrumental variable, and fixed effects regression. OLS is suitable for cross-sectional data regression and is not suitable for panel data analysis. RDD and DID are suitable for assessing the effectiveness of policies. The instrumental variables approach is suitable for solving endogeneity problems and is used in this paper in robustness tests. In contrast, fixed effects are the most suitable for this paper. In addition, this paper discusses the mechanism of the effect of the digital economy on carbon productivity using the mediator model and the threshold model. The specific research methods, indicator selection, and data sources are as follows.

3.1. Model Construction

3.1.1. Benchmark Model

In this paper, we use panel data for 285 prefecture-level cities in China, which can encounter problems that cannot be ignored, such as geographical location and other factors. These factors vary individually and not over time, which may affect the level of carbon productivity, so we control for individual fixed effects in the panel data. Similarly, the macro-environmental policy of each prefecture-level city varies over time, so we address this issue by controlling for time-fixed effects. Therefore, in this paper, we refer to Han et al. [16] and use a two-way fixed model to analyze the impact of digital economy development on carbon productivity. The model is constructed as follows.

$$Lncp_{it} = \alpha_0 + \alpha_1 Dige_{it} + \gamma control_{it} + \mu_{it} + \lambda_{it} + \varepsilon_{it} \quad (1)$$

In Equation (1), $Lncp_{it}$ is the explained variable, indicating the carbon productivity level of each city; $Dige_{it}$ is the core explanatory variable, indicating the level of digital economic development of each city; $Control_{it}$ represents the control variable; i represents the city; t represents the time; α_0 is a constant; μ_{it} is a region fixed effect; λ_{it} is a time fixed effect; ε_{it} is a random perturbation.

3.1.2. Intermediary Model

Based on the previous theoretical analysis, it is known that the digital economy affects carbon productivity through mediating variables. To verify this mechanism, we need to construct a mediating mechanism model. We refer to the method of Wen and Ye [55], first regress the mediating variable as the dependent variable and use the digital economy to regress the mediating variable. Then, the mediating variable is added to the model (1) and regressed as a control variable. The model is constructed in Equations (2) and (3).

$$M_{it} = \beta_0 + \beta_1 Dige_{it} + \gamma control_{it} + \mu_{it} + \lambda_{it} + \varepsilon_{it} \quad (2)$$

$$Lncp_{it} = \pi_0 + \pi_1 Dige_{it} + \pi_2 M_{it} + \gamma control_{it} + \mu_{it} + \lambda_{it} + \varepsilon_{it} \quad (3)$$

In Equations (2) and (3), M_{it} represents the mediating variable; other variables define the same Equation (1); $\beta_1 \times \pi_2$ denotes the mediating effect that digital economic development impacts carbon productivity by influencing the mediating variables.

3.1.3. Threshold Model

To verify how threshold variables play a threshold effect in the impact of the digital economy on carbon productivity, we need to construct a threshold mechanism model. Drawing on Li and Wang [56], we first assume the existence of a triple threshold effect. Then, we examine whether the threshold variables' effect on digital economy development on carbon productivity has different results at different levels. The threshold effect must be determined based on the threshold regression results. The threshold regression model is constructed as shown in Equation (4).

$$\begin{aligned} Lncp_{it} = \theta_0 + \theta_1 Dige_{it} I(T_{it} < \delta_1) + \theta_2 Dige_{it} I(\delta_1 \le T_{it} < \delta_2) \\ + \theta_3 Dige_{it} I(T_{it} \ge \delta_2) + \gamma control_{it} + \mu_{it} + \lambda_{it} + \varepsilon_{it} \end{aligned} \quad (4)$$

In Equation (4), T is the threshold variable. δ is the threshold value, and $\delta_1 < \delta_2$, $I(\cdot)$ is the exponential function, when the condition is satisfied then I = 1, otherwise I = 0.

3.2. Variable Definition

3.2.1. Explained Variables

Carbon productivity (Lncp) is expressed using regional GDP/carbon emissions and logged. Carbon emissions are expressed using the consumption of fossil fuels (raw coal, crude oil and natural gas) multiplied by the corresponding carbon conversion factor [57].

3.2.2. Explained Variables

The core explanatory variable of this paper is digital economy (Dige). Currently, there is no unified standard for measuring the level of digital economy development. The mainstream research perspective is on measuring digital economy development at the provincial level, with relatively few studies starting from the prefecture level. Therefore, in order to comprehensively measure the level of digital economy development in cities, this paper draws on the research methods of Zhao et al. [58] and Xu et al. [23], considers the principles of data relevance and availability, and proposes to select indicators from four dimensions to comprehensively measure the level of digital economy development (Table 1). Finally, the entropy-TOPSIS method measures the level of digital economy development in cities.

3.2.3. Intermediary Variable

There are three mediating variables in this paper. Technological innovation (Innova), using the number of utility model patents granted per 100,000 people in the year in cities [59]. Energy intensity (Energy) is expressed as each city's electricity consumption per unit of GDP [13]. Urban productivity (Efficiency) is expressed as the sum of the output value of secondary and tertiary industries divided by the total employment in secondary and tertiary industries [60].

3.2.4. Threshold Variable

There are two threshold variables in this paper: Marketization (Market), using the China Marketization Index measured by Wang et al. [61], and Human capital (HC), using the ratio of the number of students enrolled in general tertiary education to the regional population [62,63].

Table 1. Comprehensive evaluation index system of digital development degree.

Primary Indicators	Secondary Indicators	Measurement Method	Unit	Attribute
Digital Infrastructure	Internet Penetration Rate	Internet broadband access subscribers per 10,000 population	Household	+
	Mobile Subscription	Mobile phone subscribers per 10,000 population	Household	+
Digital Industry	Information Industry Foundation	Number of employees in information transmission, computer services and software industry	Ten thousand	+
	Telecommunication Industry Development	Telecommunications revenue	Million	+
Digital Innovation	Foundations of Digital Innovation	Science and technology expenditure	Million	+
	Digital High-Tech Penetration	Level of penetration of digital high-tech applications in listed companies	Times	+
Digital Inclusive Finance	Coverage	Digital Inclusion Financial Breadth of Coverage Index	-	+
	Depth	Digital Inclusive Finance Usage Depth Index	-	+
	Digitization	Digital Inclusive Finance Digitization Index	-	+

3.2.5. Control Variable

In order to analyze the impact of digital economic development on carbon productivity more accurately, the following variables are controlled. (1) Level of economic development (Lnrgdp), measured by regional real GDP per capita, is treated with 2011 as the base period. China's economic growth is predominantly sloppy, and the increased level of industrialization brings serious carbon emission problems, which may constrain the carbon productivity level. (2) The squared level of economic development ($Lnrgdp^2$) is measured using the real GDP per capita square. According to the "environmental Kuznets curve" theory, economic development will reduce pollution and increase carbon productivity when economic development reaches a certain level. (3) Industrial structure (IS) is measured by the ratio of tertiary output to secondary output. As the "factory of the world," China has a large share of industry in the economy, and most cities rely on industry to drive economic growth, which may reduce carbon productivity. (4) Openness to the outside world (OPEN) is measured by the total import and export trade ratio to GDP. Foreign-invested enterprises are restricted by the environmental policies of their home countries to transferring high-energy-consuming and high-polluting industries to developing countries, which may cause the "pollution paradise" effect and reduce carbon productivity levels. (5) Government support (GOV) is measured by the proportion of government public finance expenditure to the year's GDP. Achieving economic growth is an essential task for local governments, which may cause them to sacrifice some environmental benefits for economic benefits, resulting in lower carbon productivity levels. (6) Urbanization level (UR) is measured using the ratio of the urban population to the regional population. Higher urbanization levels increase carbon emission pressure and may reduce carbon productivity.

3.3. Data Sources and Descriptive Statistics

This paper's sample period is 2011–2019, and 285 prefecture-level cities (excluding Hong Kong, Macao and Taiwan) are selected for the study. The data of the selected indicators in this paper are mainly obtained from the 'China Urban Statistical Yearbook (2012–2020)', China Carbon Accounting Database (CEADs) and the statistical yearbooks and bulletins of each prefecture-level city. Among them, data related to the degree of digital high-tech application penetration among listed companies were obtained from the Digital Economy Research Database of CSMAR, and data related to inclusive digital finance were obtained from the Digital Inclusive Finance Index compiled by the Digital Finance Research Centre of Peking University at the prefecture level and city level. Individual missing values were filled in by linear interpolation, while each indicator was logarithmically processed. Table 2 shows the descriptive statistics of the main variables.

Table 2. Descriptive statistics.

Variables	Obs	Mean	Std	Min	Max
lnce	2565	10.233	0.730	7.559	13.117
Dige	2565	0.034	0.049	0.004	0.852
Innova	2565	0.614	1.269	0.003	19.976
Energy	2565	0.079	0.125	0.004	2.520
Efficiency	2565	3.784	1.745	0.234	19.808
Market	2565	6.886	1.719	−0.230	11.400
HC	2565	190.152	246.983	0.260	1445.798
Lnrgdp	2565	10.719	0.591	8.773	15.675
$Lnrgdp^2$	2565	115.25	12.815	76.964	245.712
IS	2565	1.003	0.577	0.114	5.340
OPEN	2565	0.197	0.344	0.000	6.915
GOV	2565	0.249	0.269	0.044	6.041
UR	2565	55.142	14.868	21.400	100

4. Empirical Result

4.1. Benchmark Regression

Table 3 reports the results of the two-way fixed effects regressions of the impact of digital economy development on carbon productivity. Columns (1)–(7) progressively include control variables, and the regression results show that both explanatory and control variables pass the significance test at the 1% statistical level. We interpret the results around column (7). The coefficient of the digital economy is 1.118, which means that for each unit increase in the digital economy, carbon productivity increases by 1.118 units, indicating that the development of the digital economy can significantly increase the level of carbon productivity, and Hypothesis 1 is verified. In the process of digital economy development, the improvement of digital infrastructure and the development of digital industry lay the foundation for the digital transformation of traditional industries and continuously adjust the energy consumption structure while prompting the optimization and upgrading of industries. At the same time, the penetration of the digital economy makes the regions more closely connected and the efficiency of resource allocation improves, which improves the optimization of industrial production efficiency and urban energy utilization, thus improving the carbon productivity level of cities. This finding is consistent with existing studies [56].

Observe the control variables. The coefficient of the primary term of the level of economic development is −2.358, which is significant at the 1% statistical level. The coefficient of the quadratic term of economic development level is 0.097, which is significant at the 1% statistical level. This indicates a significant U-shaped relationship between the level of economic development and carbon productivity, and the theory of the "environmental Kuznets curve" is verified. The inflection point is calculated at 12.155. At this stage, China's urban economic development is still in the transition stage, and the economic development mode is relatively sloppy, and the economic growth will reduce carbon productivity. When economic development reaches a certain level, the economic structure will be optimized, and carbon productivity will be increased [64]. The coefficient of industrial structure is −0.109, which is significant at the 1% statistical level, indicating that the industrial structure at this stage is not conducive to carbon productivity improvement, probably because the economic development of most cities still relies on industry. However, the industrial level of most cities is low, and the level of technology restricts productivity improvement, reducing carbon productivity. The coefficient of openness is −0.219, which is statistically significant at 1%, indicating that the foreign enterprises attracted by openness are mostly high-energy-consumption and high-pollution enterprises, which will produce the "pollution paradise" effect and thus reduce carbon productivity. The coefficient of government support is −0.282, and it passes the 1% significance level test, which indicates that economic growth is the primary goal of government spending. Some environmental quality will be sacrificed to promote urban economic development. The coefficient of urbanization level is −0.033 and passes the 1% significance level test, which indicates that the increase in urbanization level implies an increase in the number of urban residents, which leads to an expansion of energy consumption demand, corresponding to an increase in fossil energy consumption, which leads to an increase in carbon emissions and ultimately to a decrease in carbon efficiency [65].

Table 3. Benchmark regression results.

Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Dige	2.507 *** (6.29)	2.500 *** (6.32)	2.104 *** (5.37)	2.145 *** (5.50)	1.627 *** (4.12)	1.617 *** (4.14)	1.118 *** (2.86)
Lnrgdp		−0.213 *** (−5.49)	−3.311 *** (−9.38)	−3.483 *** (−9.87)	−3.400 *** (−9.71)	−3.214 *** (−9.25)	−2.358 *** (−6.55)
$Lnrgdp^2$			0.136 *** (8.82)	0.142 *** (9.21)	0.138 *** (9.05)	0.130 *** (8.57)	0.097 *** (6.22)
IS				−0.149 *** (−4.95)	−0.149 *** (−5.00)	−0.109 *** (−3.63)	−0.109 *** (−3.68)
OPEN					−0.281 *** (−6.45)	−0.232 *** (−5.31)	−0.219 *** (−5.08)
GOV						−0.271 *** (−6.93)	−0.282 *** (−7.30)
UR							−0.033 *** (−7.79)
City FE	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES
R-squared	0.4619	0.4690	0.4866	0.4921	0.5013	0.5116	0.5243
Observations	2565	2565	2565	2565	2565	2565	2565

Notes: t-statistics in parentheses; *** $p < 0.01$.

4.2. Robustness Test

4.2.1. Replace Explained Variable

In the previous paper, carbon productivity was used as the explained variable. Because the economic development level of different regions is quite different, carbon productivity per capita is used to replace the original explained variable. The regression results are in columns (1) and (2) of Table 4. The effect of digital economy development on enhancing carbon productivity still holds regardless of whether control variables are added. It passes the 1% significance test, proving that the baseline regression results are robust.

Table 4. Robustness test.

Variables	Replace Explained Variable		Replace Explanatory Variable		Tool Variable	
	(1)	(2)	(3)	(4)	(5)	(6)
Dige	3.062 *** (7.16)	1.528 *** (3.91)	0.047 *** (5.23)	0.036 *** (4.08)	4.721 *** (8.11)	3.025 *** (4.19)
Lnrgdp		−1.644 *** (−4.57)		−1.716 *** (−3.09)		−1.671 *** (−4.26)
Lnrgdp^2		0.107 *** (6.89)		0.068 *** (2.96)		0.068 *** (4.07)
IS		−0.111 *** (−3.74)		−0.120 *** (−3.23)		−0.118 *** (−2.68)
OPEN		−0.222 *** (−5.15)		−0.127 ** (−2.42)		−0.172 *** (−5.08)
GOV		−0.274 *** (−7.10)		−0.132 *** (−3.14)		−0.248 ** (−2.22)
UR		−0.041 *** (−9.65)		−0.090 *** (−6.62)		−0.029 *** (−6.03)
Kleibergen–Paap rk LM statistic					11.827 [0.001]	12.278 [0.001]
Kleibergen–Paap rk Wald F statistic					148.349 {16.38}	125.108 {16.38}
City FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
R-squared	0.4243	0.5594	0.5672	0.6077	0.0495	0.5089
Observations	2565	2565	1132	1132	2142	2142

Notes: [] values are p-values and {} values are critical values at the 10% level of the Stock-Yogo weak identification test; *** $p < 0.01$, ** $p < 0.05$.

4.2.2. Replace Explanatory Variable

In the previous section, we measured the level of digital economy development by constructing a comprehensive index system. Here we adopt the city digital economy development index compiled by Tencent Research Institute to replace the core explanatory variables. This index is jointly compiled by Tencent Research Institute with Internet companies such as DDT, JD, Meituan, Ctrip and Buy Together. Finally, it compiles the digital economy development index of Chinese cities by integrating and analyzing the high-frequency data of several businesses of Internet companies in each city, which have been studied by some researchers as a proxy variable for the digital economy [15]. Given the data availability, the sample study period was reduced to 2016–2019. The regression results are in columns (3) and (4) of Table 4. The coefficient of digital economic development remains positive with or without the inclusion of control variables. It passes the significance test at the 1% statistical level, proving that the previous empirical results are robust.

4.2.3. Endogenous Treatment

Considering that possible endogeneity problems can interfere with the research findings, this paper draws on the methods of Zhao et al. [58]. Nunn and Qian [66] take the number of telephone sets per 10,000 people in each prefecture-level city in 1984 as the historical telecommunication base and use its interaction term with the number of national Internet users in the previous year as an instrumental variable for the digital economy development index of that city in that year. On the one hand, the number of telephone sets in 1984 represents the historical telecommunication base of the region. The local historical telecommunication base is, in turn, the root of the development of the digital economy, which will have a continuous impact on the subsequent development of the digital economy. On the other hand, with the development of communication technology, landline phones are used less and less frequently in life. Their impact on carbon productivity is minimal, satisfying the principle of exclusivity.

The regression results are shown in columns (5) and (6) of Table 4, and it can be found that the coefficient of digital economy development is still significantly positive under the consideration of endogeneity, which again supports the robustness of the previous empirical results. In addition, for the test of the original hypothesis of "insufficient identification of instrumental variables," the *p*-value of the Kleibergen–Paap rk LM-statistic is 0.001, which significantly rejects the original hypothesis. In the weak identification of instrumental variables test, the Kleibergen–Paap rk Wald F-statistic is greater than the critical value at the 10% level of the Stock–Yogo weak identification test. Overall, the above tests justify the selection of the cross-sectional term between the historical number of telephone sets in each city and the number of national Internet users in the previous year as an instrumental variable for digital economy development.

4.3. Heterogeneity Test

Considering that the level of economic development in different regions of China varies greatly, the level of digital economy development and carbon productivity levels are disparate in different geographical distributions, which has a non-negligible impact on the study of the role of digital economy on carbon productivity. To accurately analyze the impact of the digital economy on carbon productivity, this paper divides Chinese cities into eastern, central and western regions, urban cluster regions and non-urban cluster regions, and resource-based cities and non-resource-based cities, as per the work of Zhang, Fan et al. [67], and Zhang et al. [68]. The regression results are shown in Table 5.

Table 5. Heterogeneity regression results.

Variables	**Eastern Regions**	**Central Regions**	**Western Regions**	**City Clusters**	**Non-City Clusters**	**Resource-Based Cities**	**Non-Resource-Based Cities**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Dige	0.729 * (1.80)	0.110 (0.06)	1.833 (0.84)	0.984 ** (2.58)	−0.743 (−0.26)	−2.405 (−0.39)	1.148 *** (2.95)
Lnrgdp	−3.221 *** (−3.01)	−8.553 *** (−7.64)	−0.858 (−1.40)	−2.363 *** (−5.27)	−3.651 *** (−3.59)	−2.685 *** (−5.52)	−2.799 *** (−3.90)
$Lnrgdp^2$	0.132 *** (2.76)	0.387 *** (7.28)	0.037 (1.48)	0.095 *** (5.12)	0.161 *** (3.35)	0.107 *** (5.26)	0.125 *** (3.80)
IS	−0.114 (−1.62)	−0.065 * (−1.66)	−0.149 ** (−2.48)	−0.005 (−0.11)	−0.181 *** (−4.30)	−0.206 *** (−4.10)	−0.039 (−1.05)
OPEN	−0.262 *** (−4.05)	−0.247 ** (−1.96)	−0.166 ** (−2.32)	−0.169 *** (−3.89)	−0.562 *** (−4.46)	−0.263 (−1.37)	−0.212 *** (−4.96)
GOV	−0.557 *** (−3.86)	−0.174 *** (−3.68)	−0.471 *** (−5.38)	−0.440 *** (−6.66)	−0.158 *** (−3.03)	−0.204 *** (−3.48)	−0.378 *** (−6.38)
UR	−0.045 *** (−6.15)	−0.026 *** (−4.66)	−0.037 *** (−3.88)	−0.030 *** (−5.72)	−0.038 *** (−5.53)	−0.030 *** (−4.51)	−0.033 *** (−6.11)
City FE	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES
R-squared	0.5183	0.5732	0.5600	0.5481	0.5168	0.5166	0.5416
Observations	900	900	765	1413	1152	1026	1539

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4.3.1. Regional Heterogeneity

It can be seen in columns (1)–(3) that, in the eastern region, the coefficient of digital economy is 0.729, which passes the significance test at the 10% statistical level, indicating that the digital economy's development significantly improves the eastern region's carbon productivity. The earlier and more comprehensive layout of digital infrastructure and digital industry development in the eastern region enables the eastern region to fully transform its resource advantages into practical results when it has a large number of digital innovation talents and capital, and to fully integrate the advantages of the digital economy into the green development of the city, thus enabling the development of the digital economy to improve carbon productivity. Digital economic development improves carbon productivity in the central and western regions but does not pass the significance test at the 10% statistical level. On the one hand, the economic development of central and western regions is relatively lagging, and the industries that take over the industrial transfer from eastern regions are mostly high-energy-consuming and high-pollution industries, which invariably increase the regional carbon emission level and reduce carbon productivity. On the other hand, the state has increased policy support for the development of digital economy in central and western regions, such as the "channels computing resources from the east to the west" project, but due to the short time and poor foundation, cities in central and western regions are still in the period of rapid development of the digital economy [59].

4.3.2. Urban Heterogeneity

It can be seen in columns (4) and (5) that, in the urban cluster area, the coefficient of digital economy is 0.984, which passes the significance test at the 5% statistical level. It indicates that the development of the digital economy significantly improves carbon productivity in urban cluster areas. The regional central cities can gather limited resources through the "siphon effect", promote the development of the central cities first, and then form a "trickle-down effect" through the universality of the digital economy development. The "trickle-down effect" will lead to the coordinated development of cities in the region, which ultimately makes the digital economy development in urban agglomerations effectively improve carbon productivity. In the non-urban cluster areas, the coefficient of digital economy is −0.743, which does not pass the significance test. Because of the relatively lagging economic development in non-urban cluster areas, imperfect digital infrastructure buildings, low networking, and a lack of regional head cities to drive development, the impact of digital economy development on carbon productivity in non-urban cluster areas are not significant [23].

4.3.3. Resources Heterogeneity

It can be seen in columns (6) and (7) that, in resource-based cities, the coefficient of digital economy is −2.405, which does not pass the significance test. The reason may be that resource-based cities have developed industries and are highly dependent on traditional resources, which are prone to "path dependence" and the "lock-in effect." The application of digital technology can optimize energy efficiency to a certain extent. However, due to the inertia of economic development, it is difficult to change the development mode of high energy consumption and high pollution in a short period, so it is difficult for the digital economy to promote carbon productivity in resource-based cities [69]. In non-resource-based urban areas, the coefficient of digital economy is 1.148, which passes the significance test at 1% statistical level, indicating that digital economy can positively affect carbon productivity in non-resource-based urban areas. It may be because non-resource-based cities have a more reasonable industrial structure, better development of the digital economy, and a higher degree of embedding of digital technology in diversified industries, which makes it easier to exert the positive effect of the digital economy in optimizing resource allocation and improving carbon productivity [70].

5. Further Analysis

5.1. Intermediary Mechanism Test

Models (2) and (3) test the mediating effects of technological innovation, energy consumption intensity, and urban productivity. According to the theoretical analysis in the previous section, the digital economy's development will increase technological innovation, reduce the intensity of energy consumption by increasing urban production efficiency, and promote carbon productivity. However, this mediating transmission mechanism needs to be verified empirically. Therefore, this paper uses a stepwise test to verify the existence of the mediating effect between digital economy and carbon productivity and reports the specific test results using the Sobel–Goodman mediation test [55], as shown in columns (1)–(6) of Table 6.

Table 6. Intermediary effect regression results.

Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
	Innova	**Lncp**	**Energy**	**Lncp**	**Effciency**	**Lncp**
Dige	11.089 *** (19.31)	0.699 * (1.66)	−0.158 * (−1.89)	0.824 ** (2.30)	2.458 ** (2.52)	1.006 ** (2.59)
Innova		0.038 *** (2.65)				
Energy				−1.858 *** (−20.64)		
Efficiency						0.046 *** (5.47)
Lnrgdp	−2.799 *** (−5.29)	−2.252 *** (−6.22)	−0.254 *** (−3.29)	−2.831 *** (−8.54)	4.579 *** (5.09)	−2.568 *** (−7.13)
$Lnrgdp^2$	0.122 *** (5.32)	0.092 *** (5.89)	0.009 *** (2.64)	0.113 *** (7.91)	−0.172 *** (−4.43)	0.105 *** (6.74)
IS	−0.333 *** (−7.63)	−0.097 *** (−3.22)	0.036 *** (5.60)	−0.043 (−1.57)	−0.430 *** (−5.78)	−0.090 *** (−3.01)
OPEN	−0.363 *** (−5.72)	−0.205 *** (−4.74)	0.033 *** (3.57)	−0.158 *** (−3.98)	−0.413 *** (−3.83)	−0.200 *** (−4.66)
GOV	0.092 (1.62)	−0.286 *** (−7.40)	0.242 *** (29.25)	0.168 *** (4.03)	−0.654 *** (−6.78)	−0.252 *** (−6.51)
UR	−0.015 ** (−2.36)	−0.032 *** (−7.66)	0.004 *** (4.52)	−0.025 *** (−6.50)	0.021 ** (1.99)	−0.034 *** (−8.07)
City FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
R-squared	0.3640	0.5258	0.5575	0.5997	0.5127	0.5306
Observations	2565	2565	2565	2565	2565	2565
Sobel Test	0.4196 *** (z = 2.624)		0.2938 * (z = 1.881)		0.1123 ** (z = 2.286)	
Goodman-1	0.4196 *** (z = 2.621)		0.2938 * (z = 1.878)		0.1123 ** (z = 2.255)	
Goodman-2	0.4196 *** (z = 2.627)		0.2938 * (z = 1.883)		0.1123 ** (z = 2.318)	
Indirect effect	0.4196 *** (z = 2.624)		0.2938 * (z = 1.881)		0.1123 ** (z = 2.286)	
Direct effect	0.6986 *** (z = 1.658)		0.8243 ** (z = 2.296)		1.0058 *** (z = 2.585)	
Total effect	1.1182 *** (z = 2.860)		1.1182 *** (z = 2.860)		1.1182 *** (z = 2.860)	
Mediating effect	0.3753		0.2628		0.1005	

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

5.1.1. Technological Innovation

Column (1) reports the regression results for technological innovation as an explanatory variable. The estimated results show that the coefficient of digital economy development is 11.089, which is statistically significant at the 1% level. This indicates that digital economy development can significantly increase technological innovation. In column (2), technological innovation is added to the regression equation of the effect of digital economy development on carbon productivity as a mediating variable. The estimated results show that the coefficient of technological innovation is 0.038, which is statistically significant at the 1% level. It indicates that technological innovation positively correlates with carbon productivity, i.e., increasing technological innovation will help improve regional carbon productivity. Meanwhile, the coefficient of digital economy is 0.699, which is statistically significant at the 10% level. This indicates that technological innovation can play a part in mediating the effect of digital economy on carbon productivity. The digital economy can accelerate technological innovation by sharing innovative knowledge through digital information technology, thus increasing carbon productivity [71]. Finally, the Sobel test, Goodman-1 test and Goodman-2 test all pass the significance test and prove that technological innovation as a mediating mechanism is established with a mediating effect of 37.53%.

5.1.2. Energy Consumption Intensity

Column (3) reports the regression results for energy consumption intensity as an explanatory variable. The results show that the coefficient of digital economic development is −0.158, which passes the significance test at 10% statistical level, proving that digital economic development can significantly reduce energy consumption intensity. In column (4), energy consumption intensity is added as a mediating variable in the regression equation of the effect of digital economic development on carbon productivity. The estimated results show that the coefficient of energy consumption intensity is −1.858, which is significant at the 1% statistical level. It indicates that energy consumption intensity is negatively related to carbon productivity, i.e., lower energy consumption intensity will increase the regional carbon productivity level. Meanwhile, the coefficient of digital economy is 0.824, which is significant at the 5% statistical level. This indicates that the development of digital economy can continuously optimize energy demand, reduce energy consumption intensity, and thus increase carbon productivity [59]. Finally, after the Sobel test, Goodman-1 test and Goodman-2 test, it is proven that energy consumption intensity holds as a mediating mechanism with a mediating effect of 26.28%.

5.1.3. Urban Productivity

Columns (5) and (6) report the regression results for urban production efficiency as a mediating mechanism variable. In column (5), the coefficient of digital economic development is 2.458, statistically significant at the 5% level, indicating that digital economic development significantly increases urban productivity. In column (6), adding the mediating variable urban productivity to the regression equation of the effect of digital economic development on carbon productivity finds that the coefficient of urban productivity is 0.046, which is statistically significant at the 1% level. It indicates that urban production efficiency has a positive relationship with carbon productivity, and an increase in urban production efficiency can increase carbon productivity. Meanwhile, the coefficient of digital economy is 1.006, which is significant at the 5% statistical level, indicating that the development of the digital economy can optimize the allocation of production factors and improve urban production efficiency, thus improving carbon productivity [72]. Finally, the Sobel test, Goodman-1 test and Goodman-2 test prove that the energy consumption intensity is a mediating mechanism with a mediating effect of 10.05%.

5.2. Threshold Mechanism Test

According to the previous analysis, the impact of digital economy development on carbon productivity can be affected by the level of marketization and human capital. Therefore, a panel threshold model is set in this paper. In this paper, the Bootstrap iterative sampling method is used to set single and double thresholds to estimate the thresholds of marketization level and human capital level, and the results are shown in Table 7. The results show that both the level of marketability and the level of human capital pass the single threshold test at the 5% statistical level. The threshold value for the level of marketability is 6.31, and the threshold value for the level of human capital is 123.14.

Table 7. Threshold estimates and test results.

Variables	Threshold	F-Value	*p*-Value	Critical Value			Threshold Values	Confidence Interval
				10%	5%	1%		
Market	Single threshold	34.89 **	0.0167	23.0899	27.9212	37.5265	6.3100	[6.2800, 6.3200]
HC	Single threshold	41.74 **	0.0367	31.2788	37.7905	453.9240	123.1431	[120.0684, 124.2784]

Notes: ** $p < 0.05$.

5.2.1. Marketization

Table 8 shows the estimation results based on the threshold model. The results show that the impact of digital economy development on carbon productivity is significantly heterogeneous in terms of marketization and human capital after controlling for both area and time effects. Specifically, when the marketization index is less than 6.31, the coefficient of digital economy development is −4.258. It passes the significance test at the 1% statistical level, indicating that the development of digital economy harms carbon productivity at this stage. When the marketization index is more significant than 6.31, the coefficient of digital economy development is 1.088. It passes the significance test at the 1% statistical level, indicating that the development of digital economy significantly increases carbon productivity at this stage. Market-oriented reform is a gradual process that involves many aspects of market economy subjects, and the government also plays a non-negligible role in this process. During low marketization, the government played a more dominant macro-regulatory role. It contributed to the early leapfrogging development of the digital economy by concentrating superior resources to develop it vigorously. The drawbacks of government intervention are also obvious: government macro-regulation is strongly policy oriented, insensitive to changes in market information, and prone to ignore the actual demand for digital products and services in different regions. The construction and subsequent use of digital infrastructure require large amounts of electricity resources. At the same time, China's power generation mainly relies on coal power; increased demand for electricity means increased coal consumption. The excessive development of the digital economy in the case of ignoring market demand has led to a waste of resources, thereby inhibiting the improvement of carbon productivity. When marketization gradually matures, the market plays a decisive role in resource allocation, and the government provides macro guidelines. The market can effectively guide the input of resources related to the digital economy to relevant regions and industries, accelerate the production and flow of factors, and provide efficient digital technology services, thus reducing inefficient energy losses, improving energy utilization, and ultimately increasing carbon productivity [44,73]. Hypothesis 2 is verified.

5.2.2. Human Capital

When examining the level of human capital, a "U-shaped" trend is observed. Specifically, when the level of human capital is less than 123.14, the coefficient of digital economy development is −5.717. It passes the significance test at the 1% statistical level, indicating that the development of digital economy inhibits the increase of carbon productivity at this stage. When the level of human capital is more significant than 123.14, the coefficient of digital economy development is 0.95. It passes the significance test at the 5% statistical level, indicating that the development of digital economy significantly increases carbon productivity at this stage. Human capital is an essential support for technological innovation and urban productivity in prefecture-level cities. It is also crucial to regulate the digital economy to improve carbon productivity. When the level of human capital is low, the city's talent resource reserve is insufficient to support technological renewal, resulting in low production efficiency. The exact output requires more resources, while the lower level of human capital is not conducive to the role of the digital economy in regulating resource allocation. The digital dividend cannot be fully utilized, thus causing the digital economy to inhibit carbon productivity improvement. When the level of human capital is accumulated to a certain extent, cities will have more high-quality talents who can continuously develop new technologies and apply them to production life, thus improving urban productivity and reducing energy consumption intensity. In addition, highly qualified talents can fully use digital information technology and Internet platforms to break through the original information constraints, facilitate knowledge sharing, and accelerate the market application of technical knowledge, ultimately enabling the development of the digital economy to promote carbon productivity improvement [53,54]. Hypothesis 3 is verified.

Table 8. Threshold model regression results.

Threshold Variables	Mar	HC
$Dige_{it} \times I(Market_{it} < 6.31)$	−4.258 *** (−4.09)	
$Dige_{it} \times I(Market_{it} \geq 6.31)$	1.088 *** (2.80)	
$Dige_{it} \times I(HC_{it} < 123.14)$		−5.717 *** (−4.81)
$Dige_{it} \times I(HC_{it} \geq 123.14)$		0.950 ** (2.44)
Control	YES	YES
City FE	YES	YES
Year FE	YES	YES
R-squared	0.5308	0.5320
Observations	2565	2565

Notes: *** $p < 0.01$, ** $p < 0.05$.

6. Conclusions and Suggestions

6.1. Conclusions

China's economy has shifted to a stage of high-quality development, and the traditional development model of high growth and high carbon emissions is no longer in line with the new development stage; improving carbon productivity has become the primary goal of development at this stage, and the digital economy provides a new means of solving this challenge. Therefore, this paper empirically tests the digital economy to improve carbon productivity using balanced panel data of 285 prefecture-level cities from 2011–2019. It is found that the development of digital economy can significantly improve carbon productivity, and this finding still holds after a series of robustness tests such as replacing the explanatory variables, explanatory variables and introducing instrumental variables. The intermediary mechanism test finds that enhancing technological innovation, reducing energy consumption intensity, and improving urban productivity are the three primary paths for the digital economy to improve carbon productivity. Further study finds that the level of marketization and the level of human capital show significant single threshold effects in the effect of digital economy on carbon productivity, which can moderate the digital economy's contribution to carbon productivity. Heterogeneity analysis shows that digital economy can improve carbon productivity in the eastern, urban agglomeration, and non-resource-based urban areas. At the same time, it cannot exert a significant promoting effect on the central and western region, non-urban agglomeration region and resource-based urban area.

6.2. Suggestions

(1) Technological innovation, energy consumption intensity and urban productivity are three effective ways to improve carbon productivity in the digital economy. Therefore, the government should introduce various policies to encourage enterprises to innovate, improve energy use efficiency, make efforts to develop the economy and bring in talents to expand the size of cities and enhance urban productivity, and continuously improve the level of marketability and human capital so that the digital economy can give full play to the effect of enhancing carbon productivity.

(2) In the process of strengthening digital innovation and research and development, focus on the development and application of green and low-carbon technologies. On the one hand, accelerate the research and development of data-processing hardware and software such as data computing, data storage and breakthroughs in core technologies, and improve the conditions of infrastructure such as 5G base stations, cloud platforms, and big data centers in each region to punch the dividends of digital economy development. On the other hand, use digital technology to change the energy consumption structure, improve energy utilization efficiency, continuously strengthen carbon capture, carbon sequestration, CCS and other carbon reduction technologies, and promote technological innovation to enhance carbon productivity.

(3) Based on the regional differences in the digital economy's impact on carbon productivity, a digital economy development strategy should be formulated according to local conditions. For central and western regions and non-urban clusters, the government should give more policy inclination, break the industry barriers and geographical restrictions, and promote the synergistic development of digital economy in each region. At the same time, the central and western regions and non-urban clusters should take advantage of their resources, continuously introduce talent, technology and capital, and strengthen experience exchange and technical cooperation with developed regions to improve carbon emission reduction performance and eventually form a coordinated development plan for carbon emission reduction among regions.

Although this paper supplements the study of digital economy and carbon productivity and provides a theoretical and practical reference for the digital economy to promote low-carbon development and green transformation, certain limitations still need further improvement. First, this paper measures the development level of the digital economy based on four aspects: digital infrastructure, digital industry development, digital innovation capacity, and inclusive digital finance. Due to the cyclical nature of digital economy development, the early stage is mainly based on infrastructure coverage. In contrast, the later stage of development is mainly based on technology integration penetration, which changes the impact of the digital economy on carbon productivity, and subsequent studies can be conducted and extended based on data richness and the cyclical nature of digital economy further to improve the measurement of the development of digital economy. Second, this paper explores the intrinsic mechanism of the digital economy's impact on carbon productivity. However, the empirical evidence is insufficient due to the spatial limitations. More in-depth research on the impact mechanism and intrinsic mechanisms of digital impact on carbon emissions is needed in the follow-up study. Third, this paper finds that the impact of digital economy on carbon productivity has regional heterogeneity, urban heterogeneity and resource endowment heterogeneity. However, the article is limited in space and does not consider the spatial impact. The follow-up study can further explore the spatial effects of the digital economy and carbon productivity.

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