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Can the Digital Economy Achieve Low-Carbon Development? An Analysis Based on the Dual Perspectives of Reducing Emissions and Increasing Efficiency

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Abstract: The digital economy is an important driver for promoting the green transformation of the manufacturing industry, as well as a key engine for achieving China's goals of reaching peak carbon, carbon neutrality, and high-quality economic development. This study uses provincial panel data from 2011 to 2021 as research samples and empirically analyzes the impact of the digital economy on carbon emissions by constructing a two-way fixed-effects model. The research findings show that the development of the digital economy can restrain the increasing scale of carbon emissions and improve carbon efficiency. A mediation effect analysis reveals that the digital economy can achieve emission reduction and efficiency improvement through the upgrading of consumption structures, while the upgrading of energy structures has the opposite effect, increasing carbon emissions. Further, a heterogeneity analysis indicates that the carbon reduction effect of the digital economy shows a trend of being higher in the west and lower in the east, higher in the north and lower in the south, higher in provinces with high openness compared to those with low openness, and higher in provinces with a good business environment compared to those with an average business environment. Based on these conclusions, recommendations are proposed at three levels: promoting the integration of the digital economy with manufacturing; fully leveraging the effects of the digital economy in relation to upgrading energy structures and consumption structures; and exploring collaborative mechanisms for regional digital development, in order to provide a theoretical basis for the development of the digital economy and realization of the "dual carbon" goals.

Keywords: digital economy; emission reduction and efficiency improvement; energy structure upgrading; consumption structure upgrading; spillover effect

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1. Introduction

Amidst the escalating global challenges of depleting resources and worsening climate change, energy conservation and carbon reduction are gradually becoming common challenges for countries worldwide. According to statistics released by the International Energy Agency (IEA), in 2022, China's carbon dioxide emissions reached 121 tons, marking a 5.2% increase from the previous year and ranking first globally. The situation of carbon emission reduction remains severe.

In the era of the new technological revolution, the digital economy has rapidly developed with the support of information and communication technologies such as big data, the Internet of Things, and cloud computing. This rapid development has spurred various new products, formats, and models through its comprehensive integration with the real economy, gradually becoming an effective means to promote national economic growth [1]. According to the "China Digital Economy Development Research Report" released by the China Academy of Information and Communications Technology, in 2022, China's digital economy reached a scale of CNY 50.2 trillion, achieving a high growth rate of 10.3% and accounting for 41.5% of the GDP. Looking at the development of the three major industries, in 2022, the penetration rates of the digital economy in agriculture, industry, and services in China were 10.5%, 24.0%, and 44.7%, respectively. At the same time, with the deep application and innovative development of digital technologies in green development and ecological conservation, the green attributes of the digital economy have garnered widespread attention, providing new insights for achieving sustainable development.

Basing on the above arguments, this study constructs a two-way fixed-effects model to examine the direct impact of the digital economy on carbon emissions. It then conducts a heterogeneity analysis on the relationship between the digital economy and carbon emissions from three dimensions: geographic location, degree of openness, and business environment. Subsequently, a mediation effect model is constructed to examine the mechanism by which the digital economy influences carbon emissions through the pathways of energy structure upgrading and consumption structure upgrading. Finally, spatial correlation is incorporated into the research framework of the impact of the digital economy on carbon emissions to further analyze the spatial spillover effects of the digital economy on carbon emissions.

2. Literature Review

In the academic community, there are numerous studies on the relationship between the digital economy and carbon emissions, mainly focusing on three concepts. The first viewpoint suggests that the development of the digital economy aids in reducing carbon emissions. Ma et al. [2] conducted empirical research based on provincial panel data from 2006 to 2017 and found that the digital economy can curb carbon emissions. Li et al. [3] and Padmaja et al. [4] believe that the development of digital technologies, represented by information and communication technology, can mitigate the increase in carbon emissions by enhancing production efficiency and promoting industrial structural upgrading. Kalmaz et al. [5] argue that reshaping urban construction and management systems through digital technology, strengthening energy-monitoring efforts, and actively developing and utilizing new energy sources are effective ways to achieve carbon emission reduction. Wu et al. [6] assessed the impact of digital infrastructure on carbon emissions from a policy evaluation perspective and found that the "Broadband China" policy can promote energy conservation and emission reduction and contribute to the achievement of neighboring regions' carbon reduction goals.

The second viewpoint suggests that the development of the digital economy may lead to an increase in carbon emissions. Some scholars argue that the increase in carbon emissions caused by the construction of digital infrastructure far exceeds the carbon emission reductions brought about by digital economic development [7,8]. Haseeb et al. [9] used an intermediate-effect model to empirically analyze the hypothesis that information and communication technology indirectly increases carbon emissions through financial development pathways. Hamdi et al. [10] believe that the development of digital technology leads to a significant increase in electricity consumption, resulting in an increase in carbon dioxide emissions. Wang et al. [11] found that the digital economy can alleviate financing constraints, encourage digital industry operators to expand production scale, and intensify energy consumption and carbon emissions. Teng et al. [12] re-validated the "Jevons Paradox" from the perspective of digital transformation, and their results predict a significant increase in carbon emissions as manufacturing companies undergo digitalization.

The third viewpoint suggests that the relationship between the digital economy and carbon emissions is non-linear. Wang et al. [13] discovered that the impact of the digital economy on carbon emissions follows a positive "U"-shaped trend of "decreasing first and then increasing". Shobande et al. pointed out through empirical evidence that the increase in ICT has a positive temporary effect on the environment, meaning that the temporary increase in ICT usage will increase carbon emissions, while in the long term, ICT usage will reduce carbon emissions [14]. Miao Lujun et al. used multiple econometric models, based on panel data from 278 prefecture-level cities in China from 2011 to 2019, and discovered that the impact of digital economic development on carbon emissions has a non-linear relationship, showing an inverted "U"-shaped relationship. Furthermore, the non-linear impact of digital economic development on carbon emissions has a spatial effect, but compared to the local impact, the spatial spillover effect is weaker [15]. Cheng et al. found through U testing that the digital economy has a non-linear spatial spillover effect on carbon emission intensity in neighboring cities, and indirectly influences carbon emission intensity through optimizing industrial structures and promoting technological innovation [16].

The existing literature provides a theoretical basis for exploring the impact of the digital economy on carbon emissions in this study, but there are still some research gaps. Firstly, the measurement of the level of digital economic development using an indicator system often relies on previous studies, and the lack of real-time selection of measurement dimensions may lead to measurement errors. Furthermore, concerning the pathways through which the digital economy influences carbon emissions, the industrial structural upgrading path on the production side is typically a research focus. However, research on achieving carbon emission reduction through the pathway of energy structure upgrading, considering that energy consumption is a primary source of carbon emissions, is limited. Similarly, a comprehensive consideration of consumption structure upgrading on the lifestyle side should also be taken into account in these pathways. Finally, numerous factors affect the carbon emission reduction effects of the digital economy, but the discussion in the existing literature mainly focuses on differences in geographical locations, which may result in policy implementation lacking specificity.

The potential marginal contributions of this study mainly include three points: (1) The introduction of a new dimension of digital governance when constructing a comprehensive indicator system for the digital economy, providing a fresh perspective on measuring the level of the digital economy. (2) The introduction of energy structure upgrading and consumption structure upgrading from both production and lifestyle perspectives, empirically analyzing the pathways through which the digital economy impacts carbon emissions, offering new insights into the intermediary pathways towards reducing carbon emissions through the digital economy. (3) The division of the research subjects according to regional geographical locations, degree of openness, and the business environment in order to examine the heterogeneous impact of the digital economy on carbon emissions, enriching the research perspectives in heterogeneity analysis.

3. Theoretical Analysis and Research Hypotheses

3.1. The Direct Impact of the Digital Economy on Carbon Emissions

With the continuous advancement of technology and rapid development of digitization, the digital economy is becoming a new driving force for the global economy. The digital economy utilizes the integration of digital technology with economic activities in energy, the environment, and other related fields to play a role in environmental governance by achieving energy-saving objectives and reducing emissions. Relevant research indicates that the digital economy can, through the integration and innovation of digital technology, coordinate energy supply and demand, incentivize technological innovation, and transform consumption patterns, thus accelerating industrial digital development and reducing energy carbon emissions. By utilizing digital development, it directs the green transformation of energy, improves environmental pollution, and achieves high-quality development goals [17]. Specifically, the digital economy can primarily reduce urban carbon emissions through three main aspects.

Firstly, by deeply integrating digital technology to promote clean energy production. In the digital economy era, the application of digital technologies such as big data, artificial intelligence, and distributed management in production, transportation, and consumption can facilitate the rapid integration of fragmented knowledge and information, promote innovation in energy-saving and low-carbon technologies, and enhance clean energy production, thereby effectively promoting carbon reduction [18,19].

Secondly, by adjusting industrial structures to improve production efficiency. The application of digital technology can promote the transformation and upgrading of industrial infrastructure, improve the level of new technologies, efficiently utilize energy and resources, and optimize resource allocation methods, thus effectively controlling and reducing carbon emissions [20,21].

Thirdly, by effectively promoting collaboration between energy supply and consumption. Through the application of digital technology, energy collection efficiency and online connectivity can be improved, enabling the digital economy to achieve intensive, data-oriented, and refined energy supply, while fostering new energy consumption methods, promoting collaboration between energy supply and consumption, and reducing carbon emission intensity [22].

Based on the analysis above, this article proposes the following hypotheses:

Hypothesis 1a. *The development of the digital economy can reduce the scale of carbon emissions.*

Hypothesis 1b. *The development of the digital economy can increase carbon emission efficiency.*

3.2. Analysis of Digital Economy Affecting Carbon Emissions through Heterogeneous Pathway

3.2.1. Pathway of Energy Structure Upgrading

The rapid development of the digital economy provides new ideas and approaches for upgrading energy structures. The main issue with traditional energy structures is the reliance on fossil fuels, leading to increased carbon dioxide emissions and exacerbating global climate change problems. The rise of the digital economy enables the more intelligent and efficient use and distribution of energy, facilitating real-time monitoring and intelligent control of energy. This precision enables better tracking and control of energy consumption, enhancing energy efficiency and conserving energy resources [13]. Breakthroughs in new energy technologies and widespread application of digital technology enable the efficient conversion and utilization of clean energies like solar and wind power. Additionally, the burgeoning digital economy provides a new path for distributed energy generation, where intelligent grids and energy internet constructions ensure equitable and inclusive energy distribution to every user, fostering energy structure upgrades and sustainable energy development [23]. With an upgraded energy structure, enterprises can more precisely manage the energy consumption needed for desired outputs, reducing excessive consumption during production. The development of the new energy industry increases the supply of clean energy, enabling greater utilization of clean energy in production and accelerating the achievement of cleaner production, leading to reduced carbon emissions and improved efficiency.

Based on the analysis above, the following hypotheses are proposed:

Hypothesis 2a. *The digital economy reduces carbon emissions by stimulating energy structure upgrades.*

Hypothesis 2b. *The digital economy enhances carbon emission efficiency by stimulating energy structure upgrades.*

3.2.2. Pathway of Consumption Structure Upgrading

The main impact of the digital economy on the upgrading of consumption structures manifests by altering consumption patterns and demands. On the one hand, with the widespread use of digital technology, people can conveniently satisfy their daily needs through online shopping, online payments, and mobile payments, significantly improving the convenience and efficiency of consumption [24]. E-commerce platforms are gradually replacing physical stores, pushing traditional manufacturing enterprises towards internet manufacturing. By opening online stores, the labor and product transport inputs required for offline operations are reduced, leading to fewer locations emitting carbon dioxide and increasing carbon emission efficiency. On the other hand, the environmental effects of the digital economy promote an increase in environmental awareness among residents, making green consumption a new focal point [25]. The surge in demand for green products and consumers' refusal to support high-energy-consumption products from traditional manufacturing enterprises drive companies towards green transformation, resulting in a decrease in energy intensity and an increase in carbon emission efficiency.

Based on the analysis above, the following hypotheses are proposed:

Hypothesis 3a. *The digital economy reduces carbon emissions by accelerating the upgrading of consumption structures.*

Hypothesis 3b. *The digital economy enhances carbon emission efficiency by accelerating the upgrading of consumption structures.*

4. Research Design

4.1. Research Model

4.1.1. Benchmark Regression Model

In order to test the impact of the digital economy on the scale and efficiency of carbon emissions, a two-way fixed-effects model is constructed as follows:

$$Y_{it} = \alpha_0 + \alpha_1 Dig_{it} + \alpha_2 Control_{it} + \mu_i + \delta_t + \varepsilon_{it} \tag{1}$$

where i and t represent the province and year, respectively, and α_i is the coefficient of each variable. Y_{it} is the dependent variable, which represents the carbon emission scale (CO_2) and carbon emission efficiency (CE) of province i in year t. Dig_{it} is an independent variable that represents the level of digital economy development in province i in year t. $Control_{it}$ represents the control variables, including the level of economic development (GDP), government support (GOV), environmental regulation (ER), and human resources (hr). μ_i is the annual fixed effect, δ_t is the provincial fixed effect, and ε_{it} is the random perturbation term.

4.1.2. Mediator Effect Model

According to the above theoretical analysis, it can be seen that the digital economy has an indirect impact on the scale of carbon emissions and carbon emission efficiency, and the goals of carbon emission reduction and carbon efficiency can be achieved through two intermediary paths: energy structure upgrading and consumption structure upgrading. The specific model for this is constructed as follows:

$$M_{it} = \beta_0 + \beta_1 Dig_{it} + \beta_2 Control_{it} + \mu_i + \delta_t + \varepsilon_{it} \tag{2}$$

$$Y_{it} = \gamma_0 + \gamma_1 Dig_{it} + \gamma_2 M_{it} + \gamma_3 Control_{it} + \mu_i + \delta_t + \varepsilon_{it} \tag{3}$$

where M_{it} is the intermediary variable, which represents the level of energy structure upgrading (ESUP) and consumption structure upgrading (CSUP) in year t of province i. The other variables are the same as those in the above benchmark model and thus will not be repeated.

4.2. Variable Description

4.2.1. Dependent Variable

The main dependent variables in this paper are carbon emission scale (CO_2) and carbon emission efficiency (CE).

Referring to the study of Du Limin and Zhu Dongbo et al. [26], the measurement of the carbon emission scale (CO_2) adopts the calculation method published by the United Nations Intergovernmental Panel on Climate Change (IPCC), selects seven main energy indicators (including coal, coke, gasoline, kerosene, diesel, fuel oil, and natural gas) in the statistical yearbook, converts their total consumption into the equivalent consumption of standard coal, and multiplies them with carbon emission factors to obtain the total carbon emissions. The specific calculation formula for this is as follows:

$$CO_2 = \sum{}_{i=1}^{7} Ei \times CFi \times CCi \times COFi \times 3.67 \quad (4)$$

where i represents the type of energy, including raw coal, coke, gasoline, kerosene, diesel, fuel oil, and natural gas. E_i represents the total energy consumption of each province, CF_i represents the calorific value, CC_i represents the carbon content, and COF_i represents the oxidation factor. $CF_i \times CC_i \times COF_i$ represents the carbon emission factor.

Carbon emission efficiency (CE) refers to the research of Wang Xiangyan et al. [13], which is measured by the ratio of GDP to carbon emission scale for each province, and the meaning of this indicator is the GDP that can be created by consuming a unit of carbon dioxide.

4.2.2. Independent Variable

The independent variable in this paper is the digital economy (Dig). At present, there is no consensus in the academic community on the method for measuring the digital economy. Yang Gangqiang et al. [27] characterized the level of development of the digital economy by statistically counting the frequency of words related to "digital technology" in the Government Work Report. Fei et al. [28] focused on the industry level and selected seven indicators in four dimensions, including digital foundation, digital scale, digital talent, and digital technology, to build a comprehensive indicator system for quantifying the development of the digital economy. Bai et al. [29] supplemented the measurement of the level of digital economy development at the city level through nine indicators in four dimensions, including digital platforms, digital enterprises, digital output, and digital users.

Considering the availability of data, this study refers to the research results of several scholars [30–33] and selects sixteen indicators from the four dimensions of digital economy infrastructure, digital industrialization, industrial digitalization, and digital governance; assigns objective weights through the entropy weight method; and calculates the digital economy development index through weighted calculations. For details on the construction of this indicator system and the method of indicator measurement, please refer to Table 1.

In our discussion, digital governance refers to the use of digital technology and data to manage, regulate, and implement government decisions and administrative functions. This can create a favorable environment and conditions for the development of the digital economy by improving government management efficiency, optimizing public services, combating corruption, and promoting information transparency.

Firstly, digital governance can improve government efficiency and transparency. Through digital data collection, analysis, and management, the government can more effectively regulate and manage social resources, optimize policy decision-making and administrative processes, and improve the quality and efficiency of public services. These measures help to boost economic vitality, attract more investments and partners, and drive the development of the digital economy.

Secondly, digital governance can promote a virtuous cycle in the digital economy. Digital governance can provide secure and reliable technological and data infrastructure for the digital economy, strengthen cybersecurity and data protection, and enhance the innovation and competitiveness of the digital economy. At the same time, digital governance can also prevent and combat cyber-fraud, data leaks, and digital crimes through regulation and management, maintaining the order and stability of the digital economy.

Additionally, digital governance can strengthen international cooperation and competitive advantages in the digital economy. Through digital governance, governments can better coordinate international cooperation, promote the development of cross-border digital economy, expand the market space, and boost international trade opportunities. Digital governance can also enhance the international competitiveness of domestic enterprises and promote the globalization of the digital economy through regulation and standardization.

In conclusion, digital governance plays an important role in the development of the digital economy. It can optimize government management, promote the healthy development of the digital economy, strengthen international cooperation and competitive advantages, and provide a solid foundation and guarantee for the sustainable development of the digital economy.

Table 1. Comprehensive indicator system for the development of digital economy.

Primary Index	***Secondary Index***	***Index Description***
Digital economy infrastructure	*Mobile phone penetration*	*Number of mobile phone subscribers per 100 people (pcs/100 people)*
	Internet popularity	*Proportion of internet users in resident population* (%)
	Information transmission span	*Optical cable line density (km/km^2)*
	Signal coverage span	*Density of mobile phone base stations (pcs/km^2)*
	Internet broadband infrastructure	*Internet broadband access port density (pcs/km^2)*
	Investment in digital services	*Per capita fixed asset investment in information transmission, computer services, and software (CNY/person)*
Digital industrialization	*Development level of postal and telecommunications industries*	*1. Total telecommunications services per capita (CNY/person)* *2. Total postal services per capita (CNY/person)* *3. Express volume (10,000 pieces)*
	Development level of electronic information manufacturing industry	*1. Electronic information manufacturing revenue (CNY 10,000)* *2. Number of electronic information manufacturing enterprises (pcs)*
	Software and information technology services	*1. Software business revenue (CNY 10,000)* *2. Number of employees in information transmission, software, and information technology services (10,000 people)*
Industrial digitization	*Degree of enterprise digital development*	*1. Number of websites owned by enterprises (pcs)* *2. Proportion of enterprises with e-commerce transactions(%)* *3. E-commerce turnover (CYN 100 million)*
	Development level of digital financial inclusion	*1. Digital financial Reach Index* *2. Digital finance Usage Depth Index* *3. Digital finance Digitization Index*
Digital governance	*Intensity of R&D expenditure*	*Ratio of internal R&D expenditure to GDP(%)*
	Number of patent applications granted	*Number of authorized patents for inventions, utility models, and appearances (pcs)*
	Per capita years of schooling	*Average years of schooling = (number of illiterate people × 1 + number of people with primary-school education × 6 + number of people with junior high-school education × 9 + number of people with high-school and secondary-school education × 12 + number of people with a college or bachelor's degree or above × 16)/total population over 6 years old*
	Number of digital economy enterprises	*Number of legal entities in the information transmission, computer services, and software industries (pcs)*

4.2.3. Mediating Variable

The mediating variables in this paper are energy structure upgrading (ESUP) and consumption structure upgrading (CSUP).

Energy structure upgrading (ESUP) is measured by the ratio of natural gas consumption to total energy consumption in each province referring to the method of Wang Xiangyan et al. [13]. Compared with traditional fossil fuels such as coal and crude oil, natural gas consumption produces less carbon dioxide, which makes natural gas a clean energy source. Thus, an increase in the proportion of its consumption can better reflect the effect of upgrading China's energy structure.

Consumption structure upgrading (CSUP) is mainly manifested in the gradual increase in the proportion of developmental and enjoyment-oriented consumption. Referring to the methods of Qi Hongqian et al. [34] and Zhang Chi et al. [35], consumption structure upgrading is measured by the proportion of developmental consumption (including transportation and communication, education, culture and entertainment, and medical and health care) and enjoyment-oriented consumption (including daily necessities and services and other goods and services) in the total per capita consumption expenditure.

4.2.4. Control Variables

Referring to existing studies [36,37], the level of economic development, environmental regulation, government support, and human capital have been selected as control variables.

The level of economic development (GDP) is measured by the logarithm of GDP per capita. Environmental regulation (ER) is measured by the ratio of total investment in industrial pollution control to industrial added value. Government support (GOV) is measured by the proportion of local general budget expenditure in the GDP of the current year. Human resources (HR) is measured by the logarithm of the number of students enrolled in ordinary colleges and universities.

4.2.5. Data Source and Descriptive Statistics

Due to the excessive lack of data in Tibet, this paper selects the panel data of 30 provinces in China from 2011 to 2021 as the research sample, and the partial missing and abnormal data of other provinces are supplemented by interpolation. The original data were mainly derived from the *China Statistical Yearbook*, the *China Energy Statistical Yearbook*, the other statistical yearbooks of various provinces and cities, the China Carbon Accounting Database, and the China Marketization Index Database. Table 2 shows the descriptive statistical results for each variable, with the maximum value of the digital economy being 0.6916 and the minimum value being 0.0091, indicating that there are great differences in the development of the digital economy among different regions in China.

Table 2. Descriptive statistics.

Variable	Obs	Mean	Std. Dev.	Min	Max
CO_2	330	10.3129	0.7510	8.3528	12.2169
CE	330	6.0826	1.0911	3.8857	9.9276
Dig	330	0.1215	0.1101	0.0091	0.6916
Dig_1	330	0.2403	0.18189	0.0491	0.9999
esup	330	0.1091	0.0044	0.0985	0.1216
csup	330	0.4173	0.0333	0.3285	0.5018
PGDP	330	5.6299	2.8961	1.6024	18.7526
ER	330	3.9951	0.3631	1.7918	4.8203
GOV	330	0.2606	0.1133	0.1051	0.7583
HR	330	4.2825	0.8027	1.5195	5.5934

5. Empirical Results and Analysis

5.1. Benchmark Regression Results

To avoid endogeneity caused by individual differences and macro-environmental changes, this study has used a two-way fixed-effects model for regression. The regression results of the OLS model without provincial fixed effects and annual fixed effects are also displayed in Table 3 for comparison. The results of Model (1) and Model (2) show that, regardless of whether two fixed effects are included, the regression coefficient of digital economy (Dig) is significantly negative at the 1% level, indicating that the development of the digital economy can significantly reduce provincial carbon dioxide emissions. Regarding the control variables, the regression coefficient of the economic development level (PGDP) is significantly positive, indicating that higher economic activity inevitably leads to a large amount of population activity and production demand, which significantly increases energy consumption and accelerates the expansion of carbon emissions. Government support (GOV) and environmental regulation (ER) are both significantly negatively related at the 5% level, indicating that government efforts to enforce strict environmental policies and provide financial support to encourage the green transformation of traditional industries have achieved dual incentives for carbon reduction. The regression coefficient of human capital (HR) is negative but not significant, indicating that high-level technical talents are necessary for achieving low-carbon development, but the carbon emissions generated by pre-preparation work and personnel activities have not been effectively addressed. The results of Model (3) and Model (4) show that the dual fixed effects of provinces and years do not affect the significance and sign of the regression coefficient of digital economy, both of which are significantly negative at the 1% level, confirming the existence of the carbon reduction effect of the digital economy. For every 1% increase in the level of digital economy, the carbon emission efficiency increases by 1.472%. The digital economy provides technological support for efficient energy utilization, making it an important pathway to improving carbon emission efficiency. In the control variables, the regression coefficients of economic development, government support, environmental regulation, and human capital are all positive and significant at different levels, indicating that factors such as rapid economic development, effective governmental actions, and ample talent reserves have significant enhancing effects on carbon emission efficiency.

Table 3. Benchmark regression results.

Variable	(1)	(2)	(3)	(4)
	CO_2	CO_2	*CE*	*CE*
Dig	−0.579 *** (2.59)	−0.476 *** (−3.09)	5.925 *** (8.14)	1.742 *** (2.75)
PGDP	−0.127 *** (−3.33)	0.176 *** (2.48)	0.083 ** (2.28)	0.132 *** (4.16)
GOV	−1.816 *** (−7.26)	−1.106 ** (−2.06)	2.331 *** (−5.74)	0.133 ** (2.02)
ER	−0.908 *** (5.87)	−0.038 ** (−2.19)	−0.539 *** (−5.80)	0.158 *** (3.76)
HR	−1.067 ** (−2.53)	−1.768 (−1.58)	−1.442 ** (−2.10)	4.869 *** (4.19)
Constant	10.943 *** (50.62)	9.236 *** (27.05)	6.627 *** (18.88)	2.322 *** (2.89)
Annual FEs	*No*	*Yes*	*No*	*Yes*
Provincial FEs	*No*	*Yes*	*No*	*Yes*
Observations	330	330	330	330
R^2	0.616	0.981	0.521	0.951

*** represents a significance level of 1%; ** represents a significance level of 5%.

5.2. Robustness Test

The regression results above show that the development of the digital economy can reduce carbon emissions and improve carbon emission efficiency. In order to avoid spurious regression results caused by endogeneity or omitted variables, we conducted robustness tests on the baseline regression results using methods such as changing the measurement method of the digital economy, lagging the digital economy by one period, reducing the sample size, and using instrumental variable methods.

(1) Changing the measurement method of the digital economy: In the baseline regression method, the level of the digital economy is measured using entropy, but possible correlations between secondary indicators may lead to measurement errors. Principal component analysis, on the other hand, simplifies the variables by reducing dimensionality, ensuring their independence and potentially reducing errors compared to entropy. The regression results in columns (1) and (2) of Table 4 show that in a two-way fixed-effects model, the inclusion of control variables does not affect the sign and significance of the Dig regression coefficient, which is consistent with the previous regression results, passing the robustness test.

Table 4. Robustness test results.

Variable	(1)	(2)	(3)	(4)	(5)	(6)
	Changing the Digital Economy Measurement Method		*Lagging the Digital Economy by One Period*		*Reducing the Sample Size*	
	CO_2	*CE*	CO_2	*CE*	CO_2	*CE*
Dig_1	−0.524 ** (−2.37)	1.027 *** (2.96)				
L.Dig			−0.525 ** (−2.00)	1.575 ** (2.55)		
Dig					−1.114 ** (−2.51)	1.169 ** (2.48)
Constant	8.887 *** (25.33)	3.132 *** (3.76)	9.277 *** (23.64)	2.060 ** (2.23)	8.010 *** (6.45)	4.187 *** (4.89)
Control variable	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Annual FEs	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Provincial FEs	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	330	330	300	300	150	150
R^2	0.981	0.950	0.983	0.956	0.989	0.985

*** represents a significance level of 1%; ** represents a significance level of 5%.

(2) Lagging the digital economy by one period: The development of digital infrastructure, technological talent cultivation, and technology research and development all require time for preparation, and the effects of the digital economy on carbon emissions may not be realized immediately. When lagging the digital economy by one period and re-running the regression, as shown in columns (3) and (4) of Table 4, the significance and sign of the regression coefficient remain unchanged, indicating the robustness of the baseline regression results. The slightly increased size of the estimation coefficient validates the existence of lagged effects in achieving carbon emission reduction and efficiency enhancement through the digital economy.

(3) Reducing the sample size: The term "digital economy" first appeared in China in the 2017 Government Work Report, marking the rapid development of the digital economy as a new focus in economic development and academic research. This study used data from the period 2017–2021 to conduct a new regression analysis, shown in columns (5) and (6) of Table 4. The results demonstrate that the impact of the digital economy on carbon emissions is still significantly negative, and its impact on carbon emission efficiency is still significantly positive, confirming the reliability of the baseline regression results.

(4) Instrumental variable method: Reductions in carbon emissions and improvements in carbon emission efficiency are inevitable outcomes of digital economy development, which also requires the need for carbon reduction goals. However, there may exist a reverse causal relationship between them, and this study may not comprehensively consider all factors influencing carbon emissions. Therefore, instrumental variables are included in the regression analysis in order to mitigate potential endogeneity due to reverse causality and omitted variables. Following the method of Huang Qun Hui et al. [38], the quantity of post offices per 1 million people in each province in 1984 and their interaction with the national information technology service income of the previous year are used as instrumental variables for the digital economy. This choice of variables is based on the fact that in the early days of the internet, post offices were commonly used as network access points for internet service providers, influencing internet development, while the digital economy represents a new form of information and internet technology in the present era. The regression results in Table 5 show that in the weak instrumental variable test, the Kleibergen–Paap rk Wald F statistic is significantly higher than the critical value for the Stock–Yogo weak identification test with a 10% bias. In the non-identifiability test, the Kleibergen–Paap rk LM statistic *p*-values are all less than 0.01, indicating that the selected instrumental variable is effective. In the regression analysis with instrumental variables, the first-stage regression results show a correlation between the instrumental variable and the digital economy. In the second stage, the regression coefficients for the digital economy are all significant at the 1% level, with the same sign as the baseline regression results, confirming the carbon emission-reducing and efficiency-enhancing effects of the digital economy.

Table 5. Robustness test results based on the instrumental variable method.

Variable	(1)	(2)	(3)	(4)
	Stage 1 (Dig)	*Stage 2 (CO_2)*	*Stage 1 (Dig)*	*Stage 2 (CE)*
IV	3.808 *** (8.12)		6.541 *** (2.41)	
Dig		−1.373 *** (−3.38)		5.644 *** (2.62)
Constant	−0.274 *** (−5.29)	7.797 *** (7.85)	0.864 *** (3.32)	9.004 *** (4.07)
Control variable	*Yes*	*Yes*	*Yes*	*Yes*
Annual FEs	*Yes*	*Yes*	*Yes*	*Yes*
Provincial FEs	*Yes*	*Yes*	*Yes*	*Yes*
Kleibergen–Paap rk LM		61.406 [0.00]		74.532 [0.00]
Kleibergen–Paap rk Wald F		65.998 [16.38]		76.325 [16.38]
Observations	330	330	330	330

*** represents a significance level of 1%.

5.3. Analysis of Heterogeneity

Different regions, influenced by factors such as their geographical location, economic development level, and resource endowment, exhibit significant differences in the stage and level of development of the digital economy, which may lead to deviations from expected assumptions regarding the impact on carbon emissions and efficiency [39]. Therefore, this study analyzes the heterogeneous impact of the digital economy on carbon emissions and efficiency from three aspects: geographical location, degree of openness, and business environment.

(1) Geographical location: Using economic and natural geographical divisions (with the Qinling–Huaihe River as the boundary), this study classifies the 30 provinces in China into Eastern, Central–Western, Northern, and Southern regions to analyze the regres-

sion results pertaining to the digital economy in different regions. These regression results are shown in Table 6. From an economic perspective, the digital economy shows significant effects on carbon emission reduction and efficiency enhancement in both the Eastern and Central–Western regions. However, the regression coefficient of the digital economy in the East is significantly smaller than that in the Central–West region, indicating that the environmental effects of the digital economy are more pronounced in the Central–Western region. This could be due to the more mature development of the digital economy in the East, with its leading economic and technological strength nationwide and high level of industrial structure greening, limiting the space for the digital economy to achieve carbon emission reduction effects [40]. Although the level of digital economy development is lower in the Central–Western region, the concentration of resource-intensive industries and the substantial carbon emissions provide more space for the digital economy to demonstrate its green effects, leading to more significant carbon emission reduction and efficiency enhancement effects. From a natural geographical perspective, the impact of the digital economy on carbon emissions and efficiency in the Southern and Northern regions is similar to that in the Eastern and Central–Western regions. The Northern region, with high carbon emissions due to factors such as winter heating and concentrated manufacturing, can effectively address its unreasonable energy structure by developing the digital economy, promoting the development and use of clean energy, and improving energy efficiency, demonstrating stronger carbon emission reduction and efficiency enhancement effects [41].

Table 6. Regression results of heterogeneity analysis based on geographical location.

Variable	**(1)**	**(1)**	**(1)**	**(1)**	**(1)**	**(1)**	**(1)**	**(1)**
	East		***Midwest***		***North***		***South***	
	CO_2	*CE*	CO_2	CO_2	CO_2	*CE*	CO_2	*CE*
Dig	−0.200 **	0.872 *	−7.994 ***	16.253 ***	−4.402 ***	7.606 ***	−0.196 *	0.805 *
	(−2.08)	(1.82)	(−8.41)	(9.43)	(−6.21)	(4.57)	(1.74)	(1.86)
Constant	8.966 ***	6.390 ***	9.334 ***	4.633 ***	8.813 ***	3.988 ***	9.920 ***	4.860 ***
	(3.17)	(4.32)	(18.22)	(5.68)	(24.58)	(4.74)	(28.85)	(4.78)
Control variable	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Annual FEs	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Provincial FEs	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	121	121	209	209	187	187	154	154
R^2	0.998	0.963	0.971	0.944	0.984	0.979	0.993	0.965

*** represents a significance level of 1%; ** represents a significance level of 5%; * represents a significance level of 10%.

(2) Degree of openness: Openness to foreign countries is crucial for accessing the latest global developments. Foreign research and development of the digital economy has started early, and the current high level of openness provides a rare opportunity for the development of the digital economy in China. To examine the heterogeneous impact of the digital economy on carbon emissions and efficiency at different levels of openness, this study uses the proportion of actual foreign investment within the GDP to measure the degree of openness [42]. The 30 provinces are divided into high and low sub-samples based on the median level of openness each year for this regression analysis. The results in columns (1) to (4) of Table 7 show that provinces with higher levels of openness experience better carbon emission reduction and efficiency enhancement effects from the digital economy. The reason for this could be that regions with higher openness generally have advantages relating to their infrastructure, scientific and technological innovation capabilities, and talent reserves, allowing them to absorb advanced digital technology and management experiences more efficiently, promote industrial greening and diversification, and subsequently reduce their carbon emissions and improve emission efficiency. Additionally, the

technological spillover effects of foreign investment effectively reduce the costs of digital transformation for enterprises, facilitate green innovation and production activities, and help achieve carbon reduction goals.

Table 7. Regression results of heterogeneity analysis according to the degree of openness and business environment.

Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
	High Openness		***Low Openness***		***Good Business Environment***		***Simple Business Environment***	
	CO_2	*CE*	CO_2	*CE*	CO_2	*CE*	CO_2	*CE*
Dig	−6.392 ***	4.647 **	−0.167 **	0.758 *	−7.349 **	3.248 **	−5.137 ***	1.208 *
	(−7.56)	(2.37)	(−2.11)	(1.92)	(−2.09)	(2.45)	(−7.81)	(1.89)
Constant	9.175 ***	0.237 ***	9.268 ***	0.971 *	8.835 ***	2.408 ***	9.270 ***	1.840 **
	(17.72)	(2.20)	(28.75)	(1.87)	(18.13)	(3.50)	(14.49)	(2.18)
Control variable	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Annual FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Provincial FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	187	187	143	143	121	121	143	143
R^2	0.978	0.872	0.996	0.968	0.994	0.965	0.982	0.850

*** represents a significance level of 1%; ** represents a significance level of 5%; * represents a significance level of 10%.

(3) Business environment: The healthy development of the digital economy and industrial greening transformation depend on external factors such as the market environment and legal framework, collectively known as the business environment. This study uses the China Marketization Index as a proxy variable for the business environment and divides the 30 provinces into high and low sub-samples based on the median level of the business environment each year for this regression analysis [43,44]. The results in columns (5) to (8) of Table 7 show that the digital economy achieves carbon emission reduction and efficiency enhancement under favorable business environments, while the green effects in regions with standard business environments are somewhat offset by certain factors. A good business environment implies strong governmental support, quality infrastructure, and the effective allocation of market resources, all conducive to the digital economy having better environmental effects. Additionally, a sound legal system effectively protects the rights of digital technology developers and green patent holders, serving as a safeguard for the development of the digital economy.

5.4. Heterogeneous Pathway Analysis

With the premise that the digital economy can reduce carbon emissions and improve emission efficiency, this study expands on the baseline research to explore how the digital economy achieves carbon reduction and efficiency improvement through the pathways of energy structure upgrading and consumption structure upgrading.

5.4.1. Pathway of Energy Structure Upgrading

The regression results for the energy structure upgrading path are shown in columns (1) to (3) of Table 8. According to the results in column (1), the coefficient of the impact of the digital economy on energy structure upgrading (esup) is significantly negative at the 1% level, indicating that the digital economy hinders energy structure upgrading, leading to an increase in the share of coal consumption in the energy structure. Observing the regression results in column (2), we see that the coefficient of energy structure is significantly positive at the 1% level, while the coefficient of the digital economy is not significantly negative. This suggests that energy structure upgrading acts as a mediator in increasing carbon emissions, contrary to the expectation outlined in Hypothesis 2a. The reason for this might be that the early stage of digital economy development in China requires a significant amount of energy input for digital infrastructure construction, technology research and development, and digital industry development. The development of clean energy such as wind and nuclear energy requires highly favorable geographical environmental conditions and long periods of time for infrastructure construction, which cannot meet the fast-growing energy demand. As a result, the consumption of traditional fossil fuels such as coal increases significantly, leading to an increase in carbon emissions due to the digital economy. In the regression results in column (3), the coefficient of energy structure is significantly positive at the 5% level, indicating that energy structure upgrading can promote the improvement of carbon emission efficiency. The coefficient of the digital economy is significantly positive, but the absolute value has decreased compared to the baseline regression results, indicating that energy structure upgrading plays an intermediate role. Its effect percentage is calculated to be 50.88%, meaning that in the process of the digital economy improving carbon emission efficiency, 50.88% of this improvement is achieved through energy structure upgrading.

Table 8. Mechanism test results pertaining to heterogeneous pathways.

Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
	esup	***CO_2***	***CE***	***csup***	***CO_2***	***CE***
Dig	−0.003 ***	−0.287	1.720 ***	0.191 ***	−0.280 ***	1.445 **
	(−3.83)	(−1.26)	(3.15)	(5.24)	(−2.89)	(2.57)
esup		61.824 ***	80.726 **			
		(3.76)	(2.05)			
rcup					−1.062 ***	−2.142 **
					(−2.92)	(−2.16)
Constant	0.095 ***	3.339 **	−5.378	0.390 ***	9.651 ***	2.377 ***
	(79.23)	(2.08)	(−1.40)	(7.12)	(26.39)	(2.72)
Control variable	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Annual FEs	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Provincial FEs	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	330	330	330	330	330	330
R^2	0.993	0.982	0.952	0.754	0.982	0.951

*** represents a significance level of 1%; ** represents a significance level of 5%.

5.4.2. Pathway of Consumption Structure Upgrading

The regression results for the consumption structure upgrading path are shown in columns (4) to (6) of Table 8. From the results in column (4), the coefficient of the impact of the digital economy on consumption structure upgrading is significantly positive at the 1% level, indicating that the digital economy promotes consumption structure upgrading.

On one hand, the digital economy has driven the rapid development of online retail, allowing consumers to purchase a variety of goods and services through the internet. Online retail largely avoids the carbon emissions caused by the staffing and decorating of physical stores. The expansion of the range of products and services makes it easier for consumers to access emerging environmentally friendly and sustainable products.

On the other hand, the digital economy provides consumers with more information and freedom of choice. As environmental awareness and sustainable development concepts spread, consumers are more likely to purchase environmentally friendly products. Digital channels such as social media and online reviews facilitate the direct expression of consumer opinions and preferences. Simultaneously, businesses gain a better understanding of consumer attitudes and feedback, allowing them to adjust product and service strategies to cater to the market's demand for green consumption. As a result, this ultimately reduces the carbon emissions generated during the production and use of products.

Additionally, the digital economy has propelled the rapid growth of the sharing economy: more consumers utilize sharing economy models to share resources and services, and things like shared bicycles, shared power banks, and shared office spaces can help consumers utilize resources in a more environmentally friendly manner, thereby reducing meaningless emissions of CO_2 from various channels.

Observing the regression results in column (5), the coefficient of the impact of consumption structure upgrading on carbon emissions is significantly negative at the 1% level, indicating that consumption structure upgrading cultivates residents' green consumption habits, effectively reducing carbon emissions in daily life. While the coefficient of digital economy remains significantly negative, the estimated magnitude has significantly decreased compared to the baseline regression, indicating that consumption structure upgrading plays a partial mediating role in the impact of the digital economy on carbon emissions, accounting for 42.61%. Similarly, the regression results in column (6) confirm the same, showing that consumption structure upgrading acts as an intermediate mechanism in the impact of the digital economy on carbon emission efficiency, with a calculated value of 23.49% for carbon emission efficiency.

5.5. Further Analysis: Spatial Effects of the Digital Economy on Carbon Emissions

Due to the unrestricted dissemination of digital elements by spatial and temporal factors, and the susceptibility of carbon emissions to influences from neighboring areas [45], this study constructs a spatial Durbin model to test whether there are spatial spillover effects of the digital economy on carbon emissions. The specific model setup is as follows:

$$Y_{it} = \alpha_0 + \alpha_1 Dig_{it} + \alpha_2 Control_{it} + W_{it}(\rho_1 Y_{it} + \rho_2 Dig_{it} + \rho_3 Control_{it}) + \mu_i + \delta_t + \varepsilon_{it} \quad (5)$$

where *Wit* is the spatial weight matrix, using both a spatial adjacency matrix and a spatial econometric matrix in regression to ensure the robustness of the regression results; $\rho 1$ represents the spatial autoregressive coefficient; and $\rho 2$ and $\rho 3$ represent the coefficients of *Dig* and the spatial interaction terms of the control variables. Other variables are the same as those in the baseline model described above, so will not be re-listed.

5.5.1. Spatial Autocorrelation Testing

Before conducting spatial panel regression, this study conducts a spatial autocorrelation test on the digital economy, carbon emission scale, and carbon emission efficiency using Moran's I index. The results of this are shown in Table 9. The spatial Moran's I index for the digital economy, carbon emission scale, and carbon emission efficiency are all positive during the study period, and they pass the significance test at the 5% level, indicating a positive spatial autocorrelation between the variables.

Table 9. Results of spatial autocorrelation test.

Year	*CO_2*		*CE*		*Dig*	
	Moran's I	*p-Value*	*Moran's I*	*p-Value*	*Moran's I*	*p-Value*
2011	0.314	0.001	0.238	0.003	0.236	0.006
2012	0.309	0.001	0.246	0.003	0.263	0.003
2013	0.306	0.001	0.215	0.005	0.234	0.006
2014	0.300	0.001	0.220	0.005	0.231	0.007
2015	0.300	0.001	0.216	0.005	0.245	0.005
2016	0.280	0.002	0.216	0.005	0.240	0.005
2017	0.272	0.003	0.194	0.008	0.229	0.007
2018	0.280	0.002	0.190	0.011	0.184	0.019
2019	0.258	0.004	0.036	0.052	0.181	0.019
2020	0.265	0.001	0.176	0.013	0.192	0.015
2021	0.224	0.004	0.171	0.013	0.206	0.011

5.5.2. Selection of Spatial Econometric Models

The spatial autocorrelation test is a prerequisite for conducting a spatial econometric analysis of the relationship between the digital economy and carbon emission scale and efficiency. Choosing the appropriate spatial econometric model is crucial for analyzing spatial effects. This study refers to the research by Elhorst [46] and conducts a series of tests to determine the specific model form, with the test results shown in Table 10. Both

LM and Robust-LM pass the significance test at the 1% level, preliminarily indicating that the spatial Durbin model (SDM) is most suitable. The Wald test strongly rejects the null hypothesis, indicating that the SDM will not degrade into spatial lag or spatial error models, further confirming the rationale for choosing the SDM. The Hausman test and LR test jointly determine that a spatial Durbin model with both province- and year-fixed effects is more suitable for the empirical research in this study.

Table 10. Test results of spatial measurement model selection.

Test Method	*Statistics*	*p-Value*	*Test Method*	*Statistics*	*p-Value*
LM SAR	45.373	0.000	*LR-SEM*	27.940	0.000
Robust-LM SAR	33.514	0.000	*Wald-SAR*	32.142	0.024
LM SEM	36.772	0.000	*Wald-SEM*	29.576	0.000
Robust-LM SEM	29.458	0.002	*Hausman*	40.032	0.000
LR-SAR	25.681	0.000			

5.5.3. Analysis of Spatial Spillover Effects

To ensure the robustness of the econometric results, this study conducts regressions using both a spatial adjacency matrix and a spatial econometric matrix. The construction of the spatial adjacency matrix is based on whether provinces are adjacent, while the spatial econometric matrix reflects the spatial relationship distance according to the difference in per capita GDP between provinces. Table 11 reports the regression results of the spatial Durbin model under the two types of spatial weight matrices. The spatial autoregressive coefficients for carbon emission scale and efficiency under both spatial weight matrices are significantly positive at the 1% confidence level, indicating positive spatial spillover effects of the carbon emission scale and efficiency between provinces. The interdependence of carbon emission scale and efficiency between neighboring provinces suggests a demonstration effect through green development, promoting an increase in carbon emission efficiency in the province [47]. The coefficient for the digital economy is significantly negative and the absolute value increases, indicating that ignoring the spatial correlation of the digital economy may underestimate its impact on carbon emission scale and efficiency. A significant negative spatial autocorrelation coefficient for the digital economy implies that the development of the digital economy in neighboring provinces can help achieve emission reduction and efficiency improvement goals in the province [48]. To further explore the impact of the digital economy on carbon emission scale and efficiency, this study decomposes its total effect into direct and indirect effects for further analysis. The direct, indirect, and total effects of the digital economy on the carbon emission scale and efficiency are all negative and pass the significance test at the 5% confidence level. Observing the effect decomposition coefficients reveals that the indirect effect accounts for over 55% of the total effect, indicating a significant green spillover effect of the digital economy, promoting green development in neighboring regions. The low-cost and rapid dissemination of digital elements, along with the positive externalities of knowledge and technology, enable associated regions to easily receive each other's digital dividends, facilitating mutual development [49].

Table 11. SDM regression results.

Variable	Spatial Adjacency Matrix		Spatial Economic Matrix	
	CO_2	CE	CO_2	CE
Dig	−0.358 ***	−2.377 ***	−0.531 ***	−2.063 ***
	(−2.72)	(4.52)	(−3.34)	(−2.87)
W × Dig	−0.361 ***	−0.559 ***	−0.481 *	−0.878 *
	(−3.34)	(−3.53)	(−1.83)	(−1.89)
ρ	0.185 ***	0.126 ***	0.125 ***	0.226 ***
	(2.99)	(−3.77)	(4.42)	(−3.74)
Direct effect	−0.383 **	−0.371 **	−0.537 ***	−0.508 ***
	(−2.31)	(−2.34)	(−3.22)	(−3.72)
Indirect effect	−0.510 **	−0.501 ***	−0.635 ***	−0.645 **
	(−2.06)	(−3.47)	(−2.92)	(−2.34)
Total effect	−0.893 **	−0.872 ***	1.172 ***	1.153 ***
	(−2.48)	(−3.31)	(−2.66)	(−2.96)
Control variable	*Yes*	*Yes*	*Yes*	*Yes*
Annual FEs	*Yes*	*Yes*	*Yes*	*Yes*
Provincial FEs	*Yes*	*Yes*	*Yes*	*Yes*
R^2	0.941	0.936	0.901	0.923

*** represents a significance level of 1%; ** represents a significance level of 5%; * represents a significance level of 10%.

6. Conclusions and Suggestions

Based on the panel data of 30 provinces in China from 2011 to 2021, this study constructed an index system for assessing digital economy and used the entropy method to measure the development level of the digital economy, and used a double-fixed-effects regression model to empirically analyze the impact of digital economy on carbon emission scale and carbon emission efficiency. The main conclusions are as follows:

(1) The digital economy can effectively reduce the scale of carbon emissions and improve carbon emission efficiency.
(2) The digital economy can achieve emission reduction and efficiency improvement through the consumption structure upgrading path, while the energy structure upgrading path increases carbon emissions instead.
(3) The impact of the digital economy on carbon emissions exhibits regional heterogeneity, with a decreasing trend from north to south and an increasing trend from east to west. Provinces with higher levels of openness experience better carbon emission reduction effects from the digital economy. Additionally, regions with good business environments show better carbon emission reduction and efficiency improvement effects from the digital economy.

Therefore, to promote green and low-carbon transformation and contribute to the achievement of "dual-carbon" goals, this study proposes the following suggestions:

Firstly, we suggest promoting the integrated development of the digital economy and manufacturing industry to cultivate new momentum for low-carbon production. Manufacturing enterprises should enhance their deep cooperation with digital technology companies and integrate digital technologies such as artificial intelligence, big data, and the Internet of Things into their manufacturing production processes in order to improve production efficiency, product quality, and achieve intelligent green transformation in the manufacturing industry.

Secondly, we suggest utilizing the energy structure upgrading effect and consumption structure upgrading effect of the digital economy. For the energy structure upgrading effect, we suggest leveraging digital technology to promote the exploitation and development of renewable energy sources and establishing a digital governance system to monitor and manage the production and consumption of renewable energy, achieving the precise use of production factors. For the consumption structure upgrading effect, we suggest developing and promoting digital services and new consumption models, thus nurturing consumers' green consumption habits, improving service levels and efficiency, and reducing resource waste and carbon emissions.

Thirdly, we suggest exploring collaborative mechanisms for regional digital development to narrow the "digital divide" between provinces. This includes establishing cooperation platforms for digital development to promote information sharing and experience exchange, jointly addressing challenges in digital development; strengthening assistance and cooperation among regions in digital technology, talent, and infrastructure construction; encouraging high-tech and digital economy-related companies to engage in cross-regional cooperation projects, share technology and resources, and enhance overall development levels; establishing professional talent training institutions or promoting cross-regional talent exchanges to address talent shortages in the process of digital development; and strengthening regional cooperation in infrastructure construction to jointly build and improve digital infrastructure, enhancing the efficiency of digital economy development.

7. Limitations

However, there are several limitations to this study. Firstly, due to limitations in data availability, our study has been conducted based on the provincial level, lacking more detailed regional units such as cities and organizations for deeper research. Secondly, as China's digital economy research started late, and the carbon-reducing effect of the digital economy requires a longer time span, our research only selected panel data spanning 11 years (2011–2021) for preliminary short-term analysis. Therefore, expanding the time dimension and increasing the sample size in future research are necessary. Thirdly, the process of the digital economy affecting carbon emissions is not unidirectional. It may show a rebound effect under the influence of different factors, which will lead to completely opposite results compared with the expectation. Thus, a non-linear study or a threshold effect study is necessary in future research.

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