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Impact of Digital Economy Development on Urban Carbon Emissions

-- Empirical Evidence and Tests for Spatial Spillovers based on Prefecture-level Cities

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Abstract

The purpose of this paper is to explore the impact of digital economy development on urban carbon emission intensity and its mechanism of action, as well as to test its spatial spillover effect and heterogeneity. Using panel data of 274 prefecture-level cities from 2008 to 2021, this paper constructs a fixed-effects model and a spatial Durbin model to assess the direct impact and spatial effect of digital economic development on urban carbon emission intensity. It is found that the development of digital economy significantly reduces the carbon emission intensity of cities, and there is a significant spatial spillover of this effect, i.e., the development of digital economy in a city not only reduces the local carbon emissions, but also has a positive emission reduction impact on neighboring cities. Further mechanism analysis shows that digital economic development reduces urban carbon emission intensity by promoting industrial structure advancedization. Heterogeneity analysis shows that digital economic development has a stronger carbon emission suppression effect on western regions and cities with lower levels of economic development. The research in this paper provides empirical evidence for understanding the role of digital economy in promoting urban green and low-carbon development, and provides a reference for formulating regional environmental policies.

Keywords

Digital Economy Development; Carbon Emission Intensity; Spatial Spillover Effect; Industrial Structure Advancement.

1. Introduction

The report of the Twentieth Party Congress states, "Actively and steadily promote carbon peaking and carbon neutrality. The realization of carbon peaking and carbon neutrality is a broad and profound economic and social systemic change." As China's major strategic decision, "dual-carbon" is not only a commitment to the international community, but also in order to promote China's high-quality economic development, in order to comprehensively promote the development of a solid foundation for green transformation. As the saying goes, "green mountains are golden mountains", for any region, only under the premise of ensuring its environmental sustainability, can more effectively guarantee the benign development of the region's social economy. At the same time, with the arrival of the digital economy era and the widespread application of the four digital technologies of artificial intelligence, blockchain, cloud computing, and big data, it has become commonplace for digital transformation to empower various industries. Although the more direct idea is that behind the growth of arithmetic power caused by the development of the digital economy is a sharp rise in the demand for electricity, however, with the proposal of the new quality of productivity as well as the green technology-enabled arithmetic power development of the practice of the landing, the National Development and Reform Commission and other four departments jointly issued the "Data Center Green Low Carbon Special Action Plan" on July 23, 2024, which clearly indicates that by the end of 2025, the national data center The layout will be more reasonable, the overall on-shelf rate will be no less than 60%, the average power utilization efficiency will be reduced to less than 1.5, and the utilization rate of renewable energy will increase by an average of 10% per year. Under the utilization of green power, energy saving and carbon reduction can be fundamentally realized. 2024 August, the State Net Information Office and other ten departments jointly issued the "Implementation Guidelines for Digitalization, Greening and Synergistic Transformation and Development", which clearly defines the main body of the implementation of the dual synergistic and the direction of the force, and provides a policy direction for the digital economy to empower the reduction of carbon dioxide and carbon reduction. Therefore, how to effectively unleash the power of digital economy on urban carbon intensity has become a hotly debated topic in academia and the community.

So, does the development of a region's digital economy reduce carbon intensity? If that effect is confirmed, what is the mechanism behind it? What are the differences in spatial patterns of the effect of digital economy development on carbon emission intensity? For these questions, the current academic research on digital economy development focuses on the following categories. First, the research about empowering the optimization and upgrading of industrial structure. Shen Yunhong and Huang Truss (2020) found that the development of digital economy promotes the upgrading and optimization of the industrial structure of the manufacturing industry through the construction of digital infrastructure and the innovation of digital technology. Wang Wen (2020) empirically examined the role of digital economy in promoting the advancement of industrial employment structure on the basis of its empowerment of industrial intelligence; secondly, research on the level of empowering enterprises. Considering that the digital economy's related digital technologies have the most direct effect on the operation and transformation of enterprises, the academic research on the microeconomic benefits of digital technologies on labor income share (Xiao Tusheng et al., 2022), performance-driven effects (Yi Luxia et al., 2021) and other microeconomic benefits is more abundant. Most of the only studies on the energy environment related to digital economy-enabled green transition focus on the enterprise level, and very few studies involve the prefecture-level city level. To answer several of the above questions, empirical studies combining empirical evidence at the prefecture-level city level on the basis of summarizing relevant theories are needed, which also provides an opportunity for this paper to make relevant marginal contributions.

The subsequent arrangement of this paper: the second part for the current academic community to sort out and summarize the relevant literature, the third part of the model setting and the description of variables, the fourth part of the empirical analysis to test whether the hypotheses are valid and relevant supporting tests, the fifth part of the further analysis, and the sixth part of the conclusions and shortcomings.

2. Literature References

The first category of literature related to this paper is to study whether digital economic development has an impact on carbon emission reduction and its mechanism of action. Guo Feng et al. (2022) empirically found that digital economic development can significantly improve urban carbon emissions, Xie Yunfei (2022) also further proposed that the improvement of the energy structure is an important mechanism for the reduction of carbon emission intensity caused by the development of the digital economy, Feng Langang et al. (2023)

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proposed that the development of the digital economy can reduce the intensity of carbon emissions through the improvement of the innovation capacity and the reduction of energy intensity, Wang Shaojian et al. (2021) proposed that the scale of output value of the secondary industry is directly proportional to the carbon emission intensity, and industrial structure adjustment is is the key to realize the overall carbon emission reduction[9] . In addition, Wang Wenju and Xiang Qifeng (2014) and Liu Zhihua et al. (2022) have conducted empirical studies on the effects of scientific and technological innovation capacity and industrial structure upgrading on carbon emission reduction, and basically a consensus has been reached. Based on the above references, the first hypothesis of this paper's research is that the development of digital economy can effectively reduce carbon emission intensity. The difference with the existing related literature is that this paper is based on the panel data of 364 prefecture-level cities from 2008 to 2021 to study the direct effect of the development of digital economy on carbon emission reduction, while the industrial structure of each city is used as a control variable. The digital economy development index is measured based on the construction idea of Liu Jun et al. (2020), which is comprehensively measured from the aspects of Internet development and digital financial inclusion.

Based on this, this paper proposes the following hypothesis H1: The development of digital economy can effectively reduce carbon emission intensity.

Another type of related literature is the research on the spatial effect of digital economy development on provincial and municipal carbon emissions, but the number of such related literature is relatively small. Some scholars first studied this issue based on provincial panel data, and then further measured the carbon emission reduction effect mechanism based on Chinese prefecture-level city panel data. Xu Weixiang et al. (2022) mentioned that the development of digital economy significantly improves urban carbon emissions and the effect is spatially heterogeneous, and Fifi Tan and Chenyu Sun (2024) further suggested that the development of digital economy has a significant positive spatial spillover effect on urban carbon emissions. Based on the above literature, this paper proposes the following hypotheses:

Hypothesis H2: The development of digital economy has a significant spatial spillover effect on the carbon emission intensity of neighboring cities.

The third category of literature related to this paper addresses the analysis of the heterogeneity of digital economic development on different regions. Wang Yongqin et al. (2018) use GDP per capita as a measure of economic development level, and regress the samples in groups by calculating the median, and Wang Shuailong (2023) draws on this method to test the nonlinear impact of the digital economy on carbon emissions in cities with different levels of economic development, and the results show that cities with low levels of economic development can enjoy the ecological dividend of their digital economy at lower levels, which is a "blessing in disguise," while cities with high levels of economic development have higher levels of digital economy development themselves, and the ecological dividend of the digital economy is "a blessing in disguise. The results show that cities with low economic development level can enjoy the ecological dividend under the low level of digital economy, which can be regarded as "sending charcoal in snow", while cities with high economic development level have a higher level of digital economy development, and the release of ecological dividend of digital economy has slowed down, so that the effect of digital economy on carbon emission reduction is more like "adding flowers to the icing on the cake". Drawing on the above references, we can infer that the western region of China is lagging behind compared with the eastern and central regions in terms of the level of economic development, and the development of the digital economy may have a more obvious carbon reduction effect on the western region.

This paper proposes hypothesis H3: Digital economic development has a more significant carbon reduction effect on the western region compared to the non-western region.

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3. Variable Selection and Modeling

3.1. Modeling

3.1.1. Baseline Regression Model

One of the core hypotheses of this paper is that the development of the digital economy can effectively reduce the intensity of urban carbon emissions, so in order to identify the relationship between them, this paper constructs the following double fixed effects model.

$$Y_{it} = \alpha_0 + \beta_1 digital_{it} + \varphi \sum control + \mu_i + \theta_t + \varepsilon_{it} \tag{1}$$

Where$i$ denotes city and$t$ denotes year. Y_{it}denotes the explanatory variable, i.e., urban carbon emission intensity. $digital_{it}$is the core explanatory variable of this paper, which indicates the level of digital economic development of the city;$control$ denotes a series of control variables that may affect the intensity of urban carbon dioxide emissions, such as the level of urbanization, the expenditure on internal R&D funding, the level of economic development, the population density, the industrial structure, the proportion of the value-added of the secondary industry to the GDP, the level of financial development, the degree of opening up to the outside world, the expenditure on the level of education, and the urban economic density, and so on, which are a series of control variables. and denote regional and time fixed variables, respectively. $\mu_i$andθ_t denote area and time fixed effects, respectively, andε_{it} denotes the random perturbation term. $\beta_1$is the coefficient of the level of urban digital economy development, which is the focus of this paper, and if it is greater than zero, it indicates that the level of urban digital economy development has a facilitating effect on the intensity of urban carbon dioxide emissions, and vice versa, it indicates that the level of urban digital economy development has an inhibiting effect on urban carbon dioxide emissions.

Equation (1) explores the total effect of digital economic development affecting carbon emission intensity, and according to the previous relevant references, it is known that digital economic development may affect urban carbon emission intensity through the intermediate path of optimizing the industrial structure, and in order to further validate the research hypothesis in this paper, the following intermediate mechanism is constructed with reference to the tests of Liu Hsing et al. (2012), Wen Chung-Lin et al. (2002), and Jiang Boat et al. (2012) Test

$$M_{it} = \alpha_0 + \beta_1 digital_{it} + \varphi \sum control + \mu_i + \theta_t + \varepsilon_{it} \tag{2}$$

$$Y_{it} = \alpha_0 + \beta_1 M_{it} + \varphi \sum control + \mu_i + \theta_t + \varepsilon_{it} \tag{3}$$

Where M is the intermediate variable, indicating the advanced industrial structure, and the other variables are consistent with the definition of variables in equation (1). When the digital economic development affects the intermediate variable and the intermediate variable affects the urban carbon emission intensity, it is considered that the digital economic development can have an impact on the urban carbon emission intensity by affecting the intermediate variable.

3.1.2. The Way the Spatial Weighting Matrix is Constructed and the Reasons for its Selection

When studying the impact of digital economy development on carbon emissions in Chinese cities, it is necessary to analyze it by using spatial econometric methods, taking into account the

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spatial spillover effect of carbon emissions. For this purpose, the elephant neighbor matrix is constructed as the spatial weight matrix. The Elephant Adjacency Matrix is a spatial weight matrix based on geographic adjacency, which is constructed as follows: ① Define adjacency: for each geographic unit (e.g., a city), determine the neighboring units with which it shares a boundary. In like adjacency matrix, only the adjacency of the shared boundary is considered, excluding the case of only shared vertices. ② Matrix representation: let the study area contain n geographic units, construct n*n square matrix W,for the elements in the matrixW_{ij} :if unit i and unit j share the boundary, then$W_{ij} = 1$,otherwise 0. ③ Normalization: in order to ensure that the sum of the weights of each unit is 1, row normalization is performed on the matrix, i.e., each element is divided by the sum of the elements of the row in which it is located.

In studying the spatial spillover effect of the digital economy, a similar spatial weight matrix construction method has been adopted in the literature. For example, when studying the spatial role mechanism of digital economy empowering double-cycle development, Wang Dongyu and Qiyong (2023) used a spatial measurement model to analyze the impact of digital economy on internal and external cycles and the transmission mechanism, emphasizing the spatial spillover effect of digital economy; Yuan Xinxin(2023) used a spatial spillover model to analyze the effect of the development level of digital economy on the industrial agglomeration in their study of the impact of digital economy on the industrial agglomeration, emphasizing the spatial radiation effect of digital economy.

These studies show that the development of the digital economy has a radiation characteristic of spreading from the center to the surrounding areas, similar to the geographic adjacency described by the image-adjacency matrix. Therefore, the construction of a spatial weight matrix using the elephant neighbor matrix helps to accurately capture the spatial spillover effect of the digital economy on carbon emissions.

3.1.3. Spatial Autocorrelation Analysis

In this study, the spatial autocorrelation analysis of total urban carbon emissions is carried out using the global Moran'I index, which was proposed by Patrick Alfred Pierce Moran in 1950, with the relevant formula as follows:

$$\boldsymbol{I = n\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}|x_i - \bar{x}||x_j - \bar{x}| \ \ / \sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}|x_j - \bar{x}|}$$

Where: the value of I ranges from [-1,1], when I is greater than 0, it means that the distribution of urban carbon emissions has a positive spatial correlation, and the larger the value, the stronger the spatial correlation, when I is less than 0, it means that the distribution of urban carbon emissions has a negative spatial correlation, and equals to 0 means that the distribution of urban carbon emissions is not spatially correlated; ,$x_i x_j$ denote the level of carbon emissions of the ith and jth cities in China;$\bar{x}$ denotes the average value; n denotes the sum of all study units.

3.1.4. Spatial Durbin Model

Since the Moran'I test shows that the Moran'I index of total urban carbon emissions is significantly positive, indicating that there is an obvious positive spatial correlation of urban carbon emissions, and if this spatial correlation is ignored when exploring the influencing factors of urban carbon emissions, bias may occur in the estimation of coefficients, so it is necessary to build a spatial econometric model. This paper constructs the following spatial Durbin model:

$$Y_{it} = \rho WY_{it} + \alpha_0 + \beta_1 digital_{it} + \beta_2 W digital_{it} + \varphi_1 \sum control + \varphi_2 \sum W control + \varepsilon_{it}$$

where ρ represents the spatial autocorrelation coefficient, reflecting the spatial dependence between the sample observations, i.e., the degree and direction of the influence of the level of digital economy development in the neighboring regions on the local carbon emissions; β_2 and φ_2 are the coefficients of the spatial interaction terms of the core explanatory variables and the control variables, respectively; and W is the spatial weight matrix of the city's neighborhoods.

3.2. Variable Selection

(1) Explained variables: the explained variable in this paper is urban carbon emissions, using urban carbon emission intensity to characterize urban carbon emissions.

(2) Core explanatory variables: this paper uses the level of urban digital economy development as the core explanatory variables, drawing on the construction ideas of Liu Jun et al. (2020), and measures the level of comprehensive development of the digital economy in terms of Internet development and digital inclusive finance. Among them, the measurement of Internet development refers to the method of Huang Qunhui et al. and adopts the entropy value to determine the weighting method to construct the relevant indexes, which is shown in Table 1 below.

Table 1. Evaluation index system for the comprehensive development level of digital economy in Chinese cities

Level 1 indicators	Secondary indicators	Tertiary indicators	Indicator properties
Overview of the digital economy Co-development index	Internet penetration	Internet users per 100 population	+
	Number of Internet-related workers	Percentage of employees in computer services and software	+
	Internet-related outputs	Total telecommunication services per capita	+
	Number of mobile Internet users	Cell phones per 100 population	+
	Digital Finance for Inclusive Development	China Digital Inclusive Finance Index	+

(3) Control variables: with reference to previous studies, other variables that may have an impact on urban CO2 emissions are controlled from the following nine points: ① urbanization level. Mark the symbol as urban; ② the level of science and technology innovation. This paper uses the internal funding of R&D to measure and take the logarithm, notation is lnRD ③ The level of economic development. This paper uses per capita regional gross domestic product to measure the level of economic development and takes the logarithm; ④ population density; ⑤ level of financial development; ⑥ value added of the secondary industry as a proportion of GDP; ⑦ level of opening up to the outside world; ⑧ expenditure on education level; ⑨ urban economic density. Descriptive statistics of variables are shown in Table 2.

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Table 2. Descriptive statistics

	Obs	Mean	SD	Min	P25	P75	Max.
carbon intensity	3836	3.86	3.77	0.192	1.491	4.723	32.204
Digital Economy Index	3836	0.31	0.80	-1.518	-0.169	0.899	3.967
urban	3836	0.51	0.20	0.000	0.413	0.631	1.000
lnRD	3836	11.77	2.02	0.000	10.690	13.121	17.185
population density	3836	5.75	0.93	0.683	5.199	6.474	7.882
industrial structure	3836	0.41	0.11	0.000	0.342	0.475	0.839
Level of financial development	3836	2.40	1.19	0.588	1.610	2.799	21.302
Level of economic development	3836	10.61	0.65	4.595	10.188	11.052	13.056
Value added of the secondary sector as a share of GDP	3836	45.99	11.60	0.000	39.594	53.377	85.079
Egypt's open-door policy towards the outside world	3836	0.02	0.02	0.000	0.004	0.025	0.229
Expenditure on education level	3836	0.18	0.04	0.000	0.151	0.204	0.377
Urban economic density	3836	0.31	0.76	0.000	0.054	0.301	15.356

4. Tests of Empirical Results

4.1. Benchmark Regression Model

According to the setting of the econometric model (1), this paper adopts a linear regression with stepwise addition of control variables to test the effect of digital economy development on urban carbon emission intensity. Considering the possible problems of heteroskedasticity and omitted variables in the test, fixed effects from the time and city levels are added to the regression, and clustered robust standard errors are used to ensure the robustness of the model. The specific estimation results are shown in Table 3 below.Column (1) of Table 3 only includes the core explanatory variable of digital economic development index and four control variables of urbanization rate, R&D expenditures, level of financial development and level of economic development, controlling for the double fixed effects of city and year, and the results show that the carbon emission intensity of digital economic development on cities is significantly negative at the 1% level. Columns (2)-(3) of Table 3, stepwise addition of a series of control variables results in significantly negative results. Column (4) adds all the control variables, and the coefficient of digital economic development is significantly negative at the 1% level, with a point estimate of -0.251. It can be seen that when the level of digital economic development increases by one unit per level of digital economic development, the carbon emission intensity of prefecture-level cities decreases by an average of 0.251 units, and Hypothesis H1 holds.

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Table 3. Benchmark regression

	(1)	(2)	(3)	(4)
VARIABLES	carbon footprint	carbon footprint	carbon footprint	carbon footprint
Digital Economy Index	-0.224***	-0.181**	-0.209***	-0.251***
	(-3.08)	(-2.30)	(-2.85)	(-3.26)
urbanization rate	-0.392	-2.658***	-0.807	-0.342
	(-0.65)	(-5.67)	(-1.35)	(-0.55)
R&D expenditures	0.016	-0.012	0.008	0.005
	(0.73)	(-0.51)	(0.39)	(0.23)
population density		0.256**	0.289***	0.221**
		(2.40)	(2.68)	(2.17)
Level of financial development	0.033	0.276***	0.010	0.021
	(0.59)	(3.11)	(0.22)	(0.45)
Level of economic development	-2.157***		-1.892***	-1.910***
	(-4.74)		(-4.29)	(-4.41)
industrialization level			-0.026***	-0.026***
			(-5.08)	(-5.14)
Egypt's open-door policy towards the outside world				1.748
				(1.58)
Expenditure on education level				2.782***
				(2.66)
Urban economic density				0.304***
				(3.26)
constant term (math.)	26.754***	3.276***	23.823***	23.556***
	(5.74)	(4.14)	(5.56)	(5.51)
observed value	3,836	3,836	3,836	3,836
R-squared	0.938	0.931	0.940	0.941
standard error of robustness	YES	YES	YES	YES
Year-level fixed effects	YES	YES	YES	YES
City-level fixed effects	YES	YES	YES	YES

Note: t-values in parentheses, ***, ** and * indicate significant at 1%, 5% and 10% confidence levels, respectively.

4.2. Heterogeneity Analysis

From Table 4 below, columns (1) and (2) categorize the cities into those in the western region and those in the eastern and central regions, as well as those with better and worse economic development. Cities in the western region and cities with poor economic development have a stronger inhibiting effect on carbon emission intensity, which also highlights the "charcoal in snow" effect of digital economic development, and also verifies the strong ability and strength of digital economic development to bridge the digital divide.

Table 4. Heterogeneity analysis

variant	(1)		(2)	
	carbon footprint		carbon footprint	
	East Central Region	western region	Areas of poor economic development	Areas with good levels of economic development
Digital Economy Index	-0.033	-1.366***	-0.617***	-0.033
	(-0.54)	(-6.61)	(-3.99)	(-0.67)
urbanization rate	1.597***	-1.736	-1.821	0.771***
	(3.60)	(-1.25)	(-1.02)	(2.61)
R&D expenditures	0.002	-0.024	-0.085**	0.013
	(0.07)	(-0.50)	(-2.24)	(0.95)
population density	-0.018	0.209*	-0.893	0.268**
	(-0.14)	(1.68)	(-1.00)	(2.53)
Level of financial development	0.012	0.263	0.092	0.234***
	(0.53)	(1.62)	(1.21)	(2.73)
Level of economic development	-1.587***	-1.699*	-2.317*	-0.804***
	(-10.36)	(-1.69)	(-1.78)	(-6.11)
industrialization level	-0.022***	-0.036***	-0.046**	-0.012***
	(-3.74)	(-5.16)	(-2.35)	(-2.88)
Egypt's open-door policy towards the outside world	2.019**	-3.716	7.275***	-0.027
	(1.99)	(-0.80)	(3.13)	(-0.03)
Expenditure on education level	3.212***	3.076	2.391	0.236
	(3.89)	(1.29)	(1.57)	(0.24)
Urban economic density	0.204***	5.183***	13.143***	0.053*
	(3.26)	(4.92)	(6.59)	(1.95)
constant term (math.)	19.805***	23.058**	35.486***	9.177***
	(11.54)	(2.30)	(3.18)	(5.45)
observed value	2,618	1,078	1,913	1,893
R-squared	0.948	0.941	0.941	0.972
standard error of robustness	YES	YES	YES	YES
Year-level fixed effects	YES	YES	YES	YES
City-level fixed effects	YES	YES	YES	YES

Note: t-values in parentheses, ***, ** and * indicate significant at 1%, 5% and 10% confidence levels, respectively.

4.3. Spatial Correlation Test and Moran Scatter Plot

In this paper, the spatial correlation of carbon emission intensity is first tested using the global Moran index, as shown in Table 5 of the Appendix. The empirical test finds that the global Moran index of carbon emission intensity is significantly positive in all 14 years from 2008 to 2021. This indicates that there is a significant positive spatial correlation of carbon emission intensity at the level of prefecture-level cities in China. Therefore, it is necessary to establish a spatial measurement model for regression analysis when empirically analyzing the effect of digital economic development on regional carbon emission intensity.

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In addition, this paper further examines the spatial clustering effect of the carbon emission intensity index by using the Moran scatter plot. It is shown in Figure 1 below. It is easy to find that the values of most prefecture-level cities are located in the first and third quadrants, indicating that the carbon emission intensity shows the spatial clustering characteristics of "high-high" and "low-low" in the distribution, which verifies the positive spatial correlation of the carbon emission intensity again. Therefore, it is further indicated that the spatial effect should be included in the analytical framework to establish a spatial econometric model to test the effect of the development of the digital economy on the regional carbon emission intensity, which precisely proves that our research needs to do spatial econometric analysis.

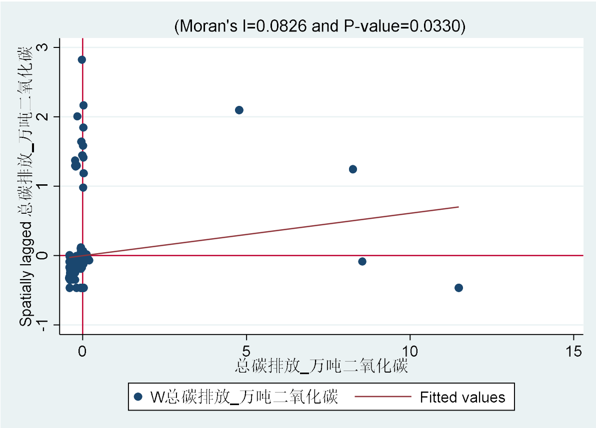

Figure 1. Scatterplot of the Moran Index

(In this paper, the Moran index test was done for 14 years, and for reasons of space, only one of the years is shown graphically.)

4.4. LM Test

Considering that the spatial econometric model contains three regression models, it is further determined whether the spatial lag model or the spatial error model should be adopted under the double fixed effects by introducing the Lagrange multiplier test (LM test). From Table 5 below, it can be seen that robust LM_test_lag passed the 1% significance test, and LM_test_sem and robust LM_test_sem passed the 1% significance test, and all three tests rejected the original hypothesis H0, which indicates that the samples selected in this paper have the double effect of spatial lag and spatial error autocorrelation. Since the SDM model takes both effects into account, which is a general form of spatial econometric modeling, it is initially judged that the selection of the spatial Durbin model (SDM) is reasonable.

Table 5. LM test

inspect	statistic	p-value
LM_test_lag	0.928	0.335
robust LM_test_lag	169.826	0.000
LM_test_sem	264.030	0.000
robust LM_test_sem	432.928	0.000

4.5. Spatial Regression Analysis

Column (1) of Table 6 below shows the results of the spatial regression without the control variables and column (2) with the control variables. It can be compared that the results after adding control variables are more significant and closer to the real situation. Therefore, this paper only analyzes the results in column (2). Analyzing from the perspective of urban carbon dioxide emission intensity, the regression coefficient of the level of digital economy development is -0.153, which passes the significance level test of 5%, indicating that the higher the level of digital economy development in the city, the lower the intensity of carbon emission in the city, which is specifically translated into the fact that for every unit of increase in the level of digital economy development in the city, the intensity of carbon emission in the city will be reduced by 0.351 units. The regression coefficient of the spatial lag term of the digital economy development level is -0.375, and it is significantly negative at the 1% level, indicating that the level of digital economy development also has a significant spatial effect on the carbon dioxide emission intensity of the city, i.e., increasing the level of digital economy development of the city can reduce the carbon dioxide emission intensity of the neighboring cities.

Table 6. Spatial regression benchmarks

	(1)	(2)
VARIABLES	carbon footprint	carbon footprint
Digital Economy Index	-0.084	-0.153**
	(-1.23)	(-2.51)
W* Digital Economy Index	-0.006	-0.375***
	(-0.07)	(-3.80)
control variable	NO	YES
urban fixed effect	YES	YES
Year fixed effects	YES	YES
Spatial	0.355***	0.294***
	(19.94)	(15.37)
Variance	0.682***	0.522
	(43.23)	(43.41)
observed value	3,836	3,836
R-squared	0.3306	0.5774

Note: z-values in parentheses, ***, ** and * indicate significant at 1%, 5% and 10% confidence levels, respectively.

5. Further Analysis

5.1. Robustness Test for Benchmark Regression

(1) Changing the time window. Consider the impact of the worldwide financial crisis in 2008 and the global health events in 2020 that may have measurement errors on the regression results. This paper conducts the regression after deleting the sample data in 2008 and 2020, and finds that the coefficient of the level of digital economic development in column (1) of Table 8 in the Appendix is -0.143, which is still significant at the 10% level, further verifying the robustness of the benchmark regression results.

(2) Replacement of explanatory variables. The digital financial inclusion index is selected for regression analysis, as shown in column (2) of Table 9, the coefficient of the digital financial inclusion index is -0.004, which is significantly negative at the 1% level, which further verifies the inhibitory effect of the level of development of the digital economy on the intensity of regional carbon emissions.

(3) Tailoring. Tailoring the sample at the 1% and 99% levels, as shown in column (3) of Table 5, the coefficient on the level of digital economic development is -0.243, and the result is still significant at the 1% level.

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Table 7. Robustness test results

	(1)	(2)	(3)
variant	carbon intensity	carbon intensity	carbon intensity
Digital Economy Index	-0.143*		-0.243***
	(-1.94)		(-3.57)
Digital Inclusive Finance Index		-0.004***	
		(-4.93)	
urbanization rate	-0.679	-0.322	0.276
	(-1.03)	(-0.51)	(0.68)
R&D expenditures	-0.000	0.003	-0.002
	(-0.01)	(0.14)	(-0.10)
population density	0.249*	0.240**	0.156*
	(1.72)	(2.35)	(1.69)
Level of financial development	0.046	0.023	0.048
	(0.94)	(0.49)	(1.26)
Level of economic development	-1.679***	-1.933***	-2.071***
	(-3.65)	(-4.42)	(-16.09)
industrialization level	-0.027***	-0.025***	-0.030***
	(-5.49)	(-5.06)	(-7.72)
Egypt's open-door policy towards the outside world	1.779*	1.215	4.496***
	(1.71)	(1.09)	(3.55)
Expenditure on education level	0.299	2.643**	1.765**
	(0.31)	(2.51)	(2.16)
Urban economic density	0.260***	0.340***	1.417***
	(2.67)	(3.26)	(11.56)
Constant	21.553***	24.085***	25.337***
	(4.62)	(5.56)	(17.34)
Observations	3,288	3,836	3,836
R-squared	0.951	0.941	0.955
cluster	YES	YES	YES
Year FE	YES	YES	YES
City FE	YES	YES	YES

Note: t-values in parentheses, ***, ** and * indicate significant at 1%, 5% and 10% confidence levels, respectively.

5.2. Robustness Tests of Spatial Econometric Models

The method of reconstructing the weights W using different spatial matrix measures. Drawing on Zhao Fang et al. (2012), the weights are proportioned by constructing an economic distance matrix.

$$W_{ij} = \frac{1}{|\ln(GDP_i - GDP_j)|}$$

where Wij is the element of the economic distance matrix. gdpi and gdpj are the per capita gdp values of the ith and jth regions, respectively.

Column (1) of Table 8 below shows the results of spatial regression without adding control variables, while column (2) with control variables added, it is not difficult to find that the regression coefficients of both are highly negative and significant, considering that the addition of control variables can better ensure that the regression equation avoids the problem of endogeneity such as omitted variable bias. Therefore, this paper only analyzes the results in column (2). Analyzing from the perspective of urban carbon dioxide emission intensity, the regression coefficient of the level of digital economy development is -0.268, which passes the significance level test of 1%, indicating that the higher the level of digital economy development in the city, the lower the carbon emission intensity in the city, which is specifically translated into the fact that for every unit of increase in the level of digital economy development in the city, the carbon emission intensity in the city will be reduced by 0.268 units. The regression coefficient of the spatial lag term of the digital economy development level is -2.418, and it is significantly negative at 1% level, indicating that the digital economy development level also has a significant spatial effect on the carbon dioxide emission intensity of the city, i.e., the increase of the digital economy development level of the city can reduce the carbon dioxide emission intensity of the neighboring cities. And the regression coefficient and explanatory power are stronger than the benchmark spatial regression, which shows that the matrix construction of economic distance matrix can more accurately measure the spatial spillover effect of digital economy on carbon emission intensity.

Table 8. Robustness analysis of the spatial economic distance matrix

	(1)	(2)
VARIABLES	carbon footprint	carbon footprint
Digital Economy Index	-0.190***	-0.268***
	(-2.66)	(-4.26)
W* Digital Economy Index	-2.494***	-2.418***
	(3.77)	(-3.13)
control variable	NO	YES
urban fixed effect	YES	YES
Year fixed effects	YES	YES
Spatial	0.355***	0.772***
	(19.94)	(13.90)
Variance	0.682***	0.559***
	(43.23)	(43.95)
observed value	3,836	3,836
R-squared	0.3798	0.2635

Note: z-values in parentheses, ***, ** and * indicate significant at 1%, 5% and 10% confidence levels, respectively.

5.3. Tests for Mediating Effects

This paper adopts the classic three-step method to test the mediating effect, which was first proposed by Wen Zhonglin et al. (2002) and further developed and improved by Jiang Boat (2012). Specifically, in the first step, this paper tests the direct impact of digital economic development on urban carbon emission intensity, and the results show that the level of digital economic development significantly reduces urban carbon emission intensity; in the second step, it tests the impact of digital economic development on industrial structure

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advancedization, and the regression results show that the level of digital economic development significantly enhances the industrial structure advancedization, with a coefficient of 0.043, and it is significant at the 5% level; In the third step, the impact of industrial structure advancedization on urban carbon emission intensity is examined, and the coefficient is found to be -0.594, which is significant at 1% level, indicating that the industrial structure advancedization significantly reduces the carbon emission intensity. In summary, digital economy development can significantly reduce urban carbon emission intensity through the mediating path of optimizing industrial structure. This result verifies the carbon reduction effect of digital economic development from the mechanism level, which further supports the hypothesis of this paper. The regression results are shown in Table 9.

Table 9. Mediating effects regression results

	(1)	(2)
VARIABLES	carbon footprint	carbon footprint
Digital Economy Index	0.043**	
	(2.26)	
urban	0.014	-0.335
	(0.08)	(-0.53)
lnRD	0.007	0.009
	(1.17)	(0.40)
population density	0.061**	0.232**
	(2.31)	(2.08)
Level of financial development	0.082***	
	(4.13)	
Level of economic development	-0.199***	-2.079***
	(-3.65)	(-4.77)
Value added of the secondary sector as a share of GDP	-0.011***	-0.033***
	(-3.49)	(-5.41)
Expenditure on education level	0.112	2.906***
	(0.64)	(2.80)
Urban economic density	-0.029***	0.263***
	(-2.61)	(3.01)
Advanced industrial structure		-0.594***
		(-3.97)
Constant	2.943***	26.131***
	(5.79)	(6.19)
Observations	3,836	3,836
R-squared	0.867	0.942
cluster	YES	YES
Year FE	YES	YES
City FE	YES	YES

Note: t-values in parentheses, ***, ** and * indicate significant at 1%, 5% and 10% confidence levels, respectively.

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6. Conclusion and Analysis of Limitations

6.1. Conclusion

The following conclusions are obtained after the analysis: ① The development of digital economy can reduce urban carbon emissions and promote the low-carbon green development of Chinese cities. ② There is a significant spatial spillover effect of the impact of digital economic development on urban carbon emissions. ③ Digital economic development has a significant inhibition effect on carbon emissions in the western region, and the degree of inhibition is significantly stronger than that in non-western regions. The possible reason is that with the development of digital economy, low economic development level cities seize the opportunities of digital economy, deepen the data elements to empower traditional elements, accelerate the integration of digital technology and energy-saving and low-carbon technology, and promote the transformation and upgrading of the industrial structure to green and low-carbon, the digital economy can be said to be "a blessing in disguise" for its carbon reduction effect; and high economic development level cities themselves digital economy development. Cities with a high level of economic development have a higher level of digital economy development, and the proportion of knowledge- and technology-intensive, green and environmental protection industries is higher, the release of ecological dividends of the digital economy has slowed down, and the digital economy's effect on carbon reduction is more of a "icing on the cake". When the development of digital economy affects the advanced industrial structure, the advanced industrial structure affects the intensity of urban carbon emissions. The development of digital economy can reduce the level of urban carbon emissions by affecting the advanced industrial structure. .

6.2. Analysis of Limitations

Although the carbon emissions in this paper pass the Moran index test and are significantly positive, indicating that there is some spatial aggregation of total carbon emissions, that is to say, cities with higher carbon emissions tend to be adjacent to other cities with higher carbon emissions, and a similar trend exists in cities with lower carbon emissions. However, the carbon emission patterns of these cities have not been further analyzed in depth to explore possible influencing factors, such as economic activities, policies, geographical characteristics, etc.; in addition, it has not been found out in which cities or urban areas there is a stronger clustering effect, so as to facilitate the formulation of more targeted environmental policies and carbon emission control strategies; the development of the digital economy has a cyclical nature, and it may be in the development stage of the infrastructure-coverage-oriented development The development of the digital economy is cyclical, and the impact of the digital economy on carbon emissions may vary between the early stages of development, when infrastructure coverage is the main focus, and the later stages of development, when technology integration and penetration are the main focus; and the measurement of the digital economy is still flawed due to the availability of data.

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