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Analysis of the Influence of Digital Economy on Carbon Emissions

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ABSTRACT

As a new modern economic system, digital economy (DE) has been extensively applied in several industries owing to its low-carbon and green characteristics. This study examines the relationship between DE and carbon emissions (CE). We collected panel data for 30 provinces in China from 2003 to 2019 to study the influence of DE on CE. The results are as follows: (1) Fixed effects model analysis shows that DE presents an overturned U-shaped relationship that indicates increased CE initially and then a gradual decrease in them. (2) Heterogeneity analysis shows that the influence of DE on CE is different in various areas, and DE in the eastern area has the most conspicuous inhibition effect on CE. (3) Spatial model analysis reveals that DE has a remarkable spatial spillover effect on CE. The growth of a DE both locally and in neighborhoods can curb CE. The study's results can help policymakers to devise policy recommendations that can reduce CE, which will help China to realize double carbon goal.

KEYWORDS

DE; Spatial effect; CE

1. HIGHLIGHTS:

(1) Panel data for 30 provinces in China from 2003 to 2019 are used.

(2) The nonlinear relationship between digital economy and carbon emissions is tested.

(3) There is a spatial correlation between digital economy and carbon emissions.

2. INTRODUCTION

Considering the deepening impact of global climatic variation on human society, countries across the world have attached great significance to the improvement of atmospheric environment and have put forward carbon neutrality at the national strategic level. The sixth disclosure of the IPCC, released in 2021, highlighted that the global temperature showed a gradual rise after the industrial revolution. The global temperature rose by 1.1˚C, and the CDE increased from 208 million tons in 1850 to 36.2 billion tons in 2019. Being the largest developing country using carbon energy in the world, China actively promotes low-carbon and green energy development to fulfill its international responsibilities. In 2020, at the 75th session of the UNGA, General Secretary proposed that green and LC characteristics are one of the important layouts of building an ecologically civilized city, and China has the vision to realize "carbon neutrality and carbon peak."

With the establishment of Chinese two carbon policies in 2020, efficient reduction of China's carbon emissions (CE) has become one of the key concerns of the society. DE is a vital way to effectively reduce Chinese CE because of its green and LC characteristics. Therefore, effective promotion of the combination of DE and LC energy industry is an important way to realize China's double carbon vision. However, as a new form of economic structure, can DE accelerate the reduction of CE in China? What are the characteristics of path and mechanism of influence? The extant literature provides the analysis of the influence of DE on CE at this stage, which mainly focuses on the characteristics research of the effect of DE on CE and the spatial effect of DE on CE. Although many studies have indicated the internal relationship between DE and CE and that DE has a prominent spatial effect on CE, there are some limitations. To answer the abovementioned questions, we used panel data for 30 provinces in China from 2003 to 2019 to study the influence of DE on CE, delve into the internal mechanism of the influence of DE on CE, and draw corresponding conclusions and suggestions to help Chinese cities develop into ecological green cities.

3. LITERATURE REVIEW AND RESEARCH HYPOTHESIS

3.1. Literature Review

With the rapid development of high-tech industries such as big information, AI, and CC, DE has become a significant part of the modern economy. Many scholars have investigated DE. There are different ways to calculate the measurement index of CE and different research ideas on the treatment of CE. The existing literature on CE mainly concentrates on whether the effect of CE trading policy is obvious, that is, the measurement method of CE. Regarding the effect of CE trading policy (CETP), Guo et al. (2022) [2]indicate that CETP is effective in stimulating CE reduction, and its effect will continually expand over time. Zhang et al. (2020) [15]show that the economic dividend of industrial output value is realized with the implementation of carbon trading policy while reducing industrial CE. Therefore, we observe that there are relatively few related studies on DE and CE at this stage. The nonlinear effect of DE on CE is the main research of current literature, as well as DE's argument about the different spatial effects of CE, and the differences in the influence of DE on CE in different areas. Meanwhile, different scholars have also made different discussions on the internal factor of the impact of DE on CE. This study provides a detailed analysis and interpretation of the above four viewpoints:

First, DE has a nonlinear effect on CE. Among the existing literature, most scholars believe that the influence of DE on CE presents nonlinear characteristics. Hao et al. (2022) [3], through research and analysis of Chinese information, show that inhibited region CE can be developed by overall DE and present a special "overturned N-type" relationship. Simultaneously, Li et al. (2021) [4] find that the influence of DE on carbon dioxide emissions presents an overturned U-shaped relationship, which confirms the hypothesis of environmental Kunets curve. Second, at present, different scholars have different degrees of study and analysis on the spatial spillover effect of DE on CE. Liu et al. (2022) [5]state that the progress of DE has a spatial spillover influence on CE efficiency, and it is affected by the progress dimension of DE. Meanwhile, Cheng et al. (2023) [1]prove the nonlinear spatial effect of DE on CE intensity of neighboring cities using the quadratic term. However, the negative spatial effect of digital technology on CEs was demonstrated by Zhang et al. (2023a) [14]from the perspective of digital technology. However, Zhong et al. (2022b) [17]use the spatial Dobbin model to study the spatial effect of DE on CE but did not provide a detailed analysis. This study uses the spatial effect of DE on CE to model and analyze it. Third, different scholars have different conclusions on the territorial heterogeneity analysis of the effect of DE on CE. Zhong et al. (2022a) [16]assert that the influence of DE on CE has different intensities at the central and peripheral nodes of the network. However, Yu et al. (2022) [13] conclude that the effect of DE on CE is heterogeneous at different levels of DE development. Meanwhile, Yan et al. (2022) [11]assert that the influence of DE on urban CE has regional heterogeneity beneath diverse levels of CE. Fourth, there are different discussions on the internal effect mechanism of DE on CE at this stage. Regarding this, Lyu et al. (2023) [6] assert that industrial structure is a momentous way for DE to affect CE, suggesting that there does not exist a unified angle to explore the internal mechanism of DE affecting CE at this stage.

To sum up, although there is a certain study foundation on the impact mechanism of DE on regional CE at this stage, the following limitations exist: First, although nonlinear impacts have been indicated in existing studies, most scholars have not discussed its internal impact mechanism extensively. Second, in spatial spillover context effect produced by DE, the conclusions are incoherent among different studies. Therefore, we applied panel data of 30 provinces in China from 2003 to 2019 to existing theories to conduct modeling and empirical analysis, investigate the influencing and internal factors of DE on CE, and analyze and explore whether there is spatial spillover effect. The study's main contributions are as follows: From the perspective of research, this study abandons the traditional perspective of simple linear relation analysis between DE and CE and fully explores the nonlinear impact of DE on CE. Regarding relation path, different from traditional simple relation analysis, this study uses threshold model to analyze and study the internal mechanism of DE on CE and explores the effect path of DE on CE. In conclusion, different spatial matrix weight perspectives are used to analyze the spatial effects of DE on CE, provide more comprehensive interspace spillover effects results, and then provide corresponding policy suggestions.

3.2. Research Hypothesis

With the rapid expansion of the Internet, CC, and other technologies, DE has become one of the main economic activities in China. As a new economic activity, DE has green, efficient, and innovative characteristics. On one hand, the progress of DE has provided a new element for various industries. With large inputs of elements of DE, the energy structure of China is continuously transforming to modernization, thus decreasing the ratio of carbon energy use and promoting reduction of CE. On the other hand, the rapid progress of DE can continuously promote innovation of LC technology and improve the efficiency of using carbon energy, thus decreasing the ratio of CE from the source. Simultaneously, according to the existing literature, the development of DE can traverse the obstacles of time and space and can realize the trans-regional flow of resources. Therefore, this study mainly provides theoretical evidence from three perspectives: the nonlinear influence of DE on CE, influence element of DE on CE, and spatial effect of the influence of DE on CE.

3.2.1. The nonlinear impact of DE on CE

DE is a modern economic activity formed by the continuous evolution of the Internet, CC, big information, and other high-tech technologies. Therefore, its evolution is bound to have a certain stage. Meanwhile, the effect on CE will be varied depending on the progress stage of DE (Qin et al. 2022) [8] According to the EKC, DE will inevitably require a considerable infrastructure investment during the initial stage of development, and the establishment of many Internet base stations, 5G base stations, and various technology research and development sites will lead to a relatively serious impact on the environment. In addition, with the construction of various base stations, electricity usage will rise, leading to increased CE. With the continuous progress of the DE, the environmental dividend of the DE has gradually emerged, and various LC technologies have been continuously realized, reducing the level of CE from the source. Meanwhile, with the efficient combination of the DE and various industries, several industries have transformed to modern structure. Using modern technologies such as big information and CC, supervision and management level of CE are constantly improved to achieve effective reduction of CE. Therefore, we derive the following hypothesis:

H1: DE has an overturned U-shaped influence on CE, which is initially accessorial and then repressed.

3.2.2. The spatial effect of the influence of DE on CE

The spatial effect of DE on CE is primarily generated through the following: First, all kinds of information break the limitation of geographical location owing to the digital characteristics of DE.

Through the Internet and modern information exchange platform, information can spread rapidly in a short time, and the exchange of technical information can be realized across different regions at a low cost, thus promoting the improvement of the overall pattern of CE. Yilmaz et al. (2021) [12]conducted empirical research through interstate panel information of the United States and showed that DE has significant spatial effect. Second, DE, owing to its digital industrial structure, avoids the geographical boundary problem among conventional industries and enables trans-regional cooperation and communication among digital industries, thus promoting the rapid expansion of the DE industries of both parties. Simultaneously, the factor endowment cooperation of DE can realize the integrity of the overall industrial structure to reduce the CE and other problems caused by the independent factors to restrain the growth of CE. Third, the cross-regional communication of DE will lead to the cluster influence of DE and industrial shift of DE in a region. Ma et al. (2022) [7]mention that DE causes the loss of regional capital when it strengthens the communication among industries. With the increasing regional capital loss, regional fiscal revenue will also be affected to a certain extent, which will reduce the financial support for CE control in the aera, thus affecting the CE control in the area (Wang et al., 2022) [10]. Fourth, DE, through the extensive exchange of modern Internet, CC, and other high-tech technologies, can bridge the digital divide among regions, promote the standard of industrial digitization among regions and the industrialization of DE, and provide more extensive coverage of LC technologies for neighboring cities to promote the reduction of CE. Hence, the following hypothesis is derived:

H2: DE has a spatial effect on CE.

4. RESEARCH DESIGN

4.1. Model Specification

We use panel data for 30 provinces in China from 2003 to 2019 to study the influence of DE on CE. Therefore, first, we establish the panel regression model of benchmark fixed effect as follows:

$$Ce_{it} = \alpha_0 + \alpha_1 Dige_{it} + \alpha_2 Dige_{it}^2 + \alpha_2 Controls_{it} + \mu_i + \delta_t + \varepsilon_{it}, \quad (1)$$

Where, i denotes the city, t denotes the year, explained variable $\mathrm{Ce_{it}}$ represents the CE of city i in year t, and the core explaining variable $\mathrm{Dige_{it}}$ denotes the development level of DE of city i year t. To verify the overturned U-shaped relationship between the core explanatory variable and explained variable, square term of the core explanatory variable is added as $\mathrm{Dige_{it}^2}$. Controls are the control variables, including Pd, Pgdp, Es, Ul, and Ugl. α_0 is the constant term, μ_i is the urban fixed influence, δ_t is the time fixed influence, and ε_{it} is the residual.

Simultaneously, to ensure the fitness and effectiveness of model selection, fixed, random, and mixed effects are used for reference regression in the basic regression, and Hausman, Wald, and F tests are used to select the three kinds of effects.

Finally, to study whether DE has a spatial effect on CE, we establish a spatial Dubin model (SDM) considering the fixed influence and decide whether to adjust the model according to the empirical results in subsequent tests. The SDM is as follows:

$$Ce_{it} = \alpha_0 + \rho WCe_{it} + \varphi_1 WDige_{it} + \emptyset_1 Dige_{it} + \varphi_2 WControls_{it} + \emptyset_2 Controls_{it} + \mu_i + \delta_t + \varepsilon_{it}, \quad (2)$$

Where ρ denotes the spatial autoregressive factor and W is the spatial weight matrix. The economic matrix (W_1), distance matrix (W_2), and population-geography matrix (W_3) are selected for analysis to boost the robustness of the empirical results. φ_1 and φ_2 are the factors of the interaction terms of the center explanatory variables and control variable space.

4.2. Variable Measurement

Considering the realizability of information and accuracy of results, we selected 30 provinces in the mainland China except Xizang to obtain panel data from 2003 to 2019. Meanwhile, to ensure that the data are not affected by the index dimension, we conducted logarithmic de-dimensional processing on the obtained information. All information in this study were mainly from CSY, CESY, and provincial statistical yearbooks. For some missing information, linear interpolation was used for missing value processing.

4.2.1. Explained variables

CE: In extant research, there are different calculation methods for measuring CE. In this study, considering the realizability of information and relevant literature, eight kinds of fossil energy such as coke, raw petroleum, and gasoline are collected and sorted through provincial statistical yearbook, and the annual total CE of each province is calculated using the CE factor of multifarious energy sources. The calculation equation is as follows:

$$CO_2 = \sum_{i=1}^{8} CO_{2i}, \tag{3}$$

Where CO_{2i} is the ith fossil fuel emission.

4.2.2. Nuclear variables

DE evolution level (Dige): The current DE measurement lacks unified standards. The study sets up three secondary dimensions, digital basics, digital industry, and digital innovation, as the indicators to measure the evolution level of DE. The digital basic dimension selects the number of mobile telephone users at the end of the year and capacity of mobile phone exchanges as the measurement indicators. The digital industry dimension selects the general number of telecom business and postal business as the measurement indicators. In the digital innovation dimension, two indicators, science and technology expenditure and special authorization number, are selected as the measurement indicators. Based on the above indicators, the synthetical level of DE is calculated by the entropy method.

Table 1. DE evaluation index system

Primary index	Secondary index	Yardstick	Index attribute
DE development level	Digital basic	The number of mobile phone users at the end of the year	+
		The total amount of telecom business	+
	Digital industry	The total amount of telecom business	+
		The total amount of postal business	+
	Digital innovation	Science and technology expenditure	+
		Special authorization number	+

4.2.3. Control variable

Considering the factors that may affect CE, this study selects six control variables, namely population density (Pd), economic development level (Pgdp), energy consumption (Power), urbanization level (Ul), urban greening level (Ugl), and energy structure (Es). Among them, the population thickness is calculated according to the proportion of total resident populace per province to regional area. The economic progress level is measured by local per capital GDP, and energy intensity is measured by local total carbon and energy consumption. The urbanism level is calculated by the percentage of the total civic population to the general population. The urban greening level is measured by the per capital green space. The energy structure is surveyed by the ratio of carbon energy use to electricity use.

Table 2. Descriptive statistics

Variable	Implication	Obs	Mean	Std	Min	Max
Ce	CE	510	4.430	0.344	3.198	5.173
Dige	DE development level	510	3.035	0.555	1.732	4.898
Dige2	DE development level 2	510	11.233	3.677	3.000	23.987
Gti	Gti level	510	2.737	0.764	0.322	4.436
Pd	Population density	510	3.342	0.272	2.270	3.800
Pgdp	Economic development level	510	4.031	0.460	2.586	5.032
Power	Energy consumption	510	3.045	0.349	1.753	3.826
Ul	Urbanization level	510	0.548	0.257	0.139	4.089
Ugl	Urban greening level	510	1.460	0.088	1.106	1.849
Es	Energy structure	510	3.045	0.349	1.753	3.826

5. EMPIRICAL ANALYSIS

5.1. Basic Regression Analysis

Table 3 shows the basic regression results of the effect of DE on CE. For the accuracy of model selection, the fixed, random, and mixed effects are used to conduct the benchmark regression. Columns (1) and (2) represent fixed effect, column (3) represents random effect, and column (4) represents mixed effect. Column (4) shows that the F-test is 622.62, which represents 1% significance level; therefore, the fixed panel is superior to the mixed panel. Column (3) shows that the Wald test value is 5097.08 and has 1% significance level; therefore, the random panel is superior to the mixed panel. The Hausman test results of column (2) show that the fixed panel is superior to the random panel at 1% significance level. We select the fixed panel model. Column (1) is the fixed panel regression result without appending control variables, and column (2) is added with control variables. According to regression consequences of model (1), the factor of the first term of the progress level of DE is positive, and the factor of the second term is negative, indicating that, with the improvement of the progress level of DE, the increase of CE will be aggravated in the inchoate stage of the progress of DE. For every per unit addition in the development level of DE, the corresponding CE will increase by 1.195 units. After the progress of DE to a certain extent, square term of the evolution level of DE will be greater than the aggravating effect generated by the level of DE, thus promoting the reduction of CE. Therefore, H1 is supported. Column (2) in Table 3, after the addition of control variables, shows that the factor of DE decreases to 0.152, and the factor of the square term of DE increases to -0.035, demonstrating that the addition of control variables separates the effect of other elements on CE.

Table 3. Benchmark regression result

Variable	FE		RE	OLS
	(1)	(2)	(3)	(4)
Dige	1.195*** (19.41)	0.152** (2.53)	0.164*** (2.69)	0.392** (2.05)
Dige2	-0.132*** (-14.48)	-0.035*** (-5.10)	-0.037*** (-5.32)	-0.077*** (-3.86)
Pgdp		-0.020 (-0.58)	-0.024 (-0.69)	-0.017 (-0.15)
Ul		0.011 (0.95)	0.008 (0.73)	-0.033 (1.40)
Power		1.215*** (21.33)	1.301*** (25.22)	1.653*** (13.44)
Es		-3.200*** (-11.45)	-3.757*** (-14.38)	-6.915*** (-8.12)
Pd		0.003 (0.28)	-0.001 (-0.12)	0.054 (1.35)
Ugl		0.187*** (3.55)	0.171*** (3.32)	0.438*** (3.85)
constant	1.965*** (19.08)	2.845*** (20.31)	3.047*** (22.66)	3.463*** (7.02)
City	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
F Test				622.62***
Wald Test			5097.08***	
Hausman Test		170.29***		
R2	0.766	0.913	0.899	0.889
Obs	510	510	510	510

Note: ***, **, and * mean obvious at 1%, 5%, and 10% significance levels, respectively. The value of t is in brackets.

Table 3 shows that. Pgdp, Pd, and Power selected as the control variables in this study are salient and have a positive impact. From empirical point of view, the higher the level of urban economic progress, the higher the relative development of city's industry, thus aggravating urban CE. The higher the energy strength and population density, the greater the demand for carbon energy, thus contributing to increased CE.

5.2. Spatial Effect Analysis

To ensure the accuracy of results, we conduct a spatial autocorrelation test before analyzing the spatial influence of DE on CE. We use Moran's I index for calculating the development level of DE and CE each year under the economic matrix. Table shows the results. We observe that the Moran's I index of the development level of DE from 2003 to 2019 under the weight of economic matrix achieved the significance level of 1%, and the Moran's I index of CE from 2003 to 2019 under the weight of economic matrix reached the significance level of 5%. Thus, we conclude that the spatial autocorrelation factors are all positive, indicating that DE and CE of Chinese cities from 2003 to 2019 have obvious spatial autocorrelation. Therefore, the relationship between DE and CE has spatial effect.

Table 4. Moran's I Index

Year	Dige			Ce		
	Moran's I	Z	P	Moran's I	Z	P
2003	0.081	3.249	0.001	0.058	2.627	0.004
2004	0.078	3.172	0.001	0.050	2.399	0.008
2005	0.082	3.265	0.001	0.049	2.404	0.008
2006	0.082	3.266	0.001	0.049	2.368	0.009
2007	0.090	3.480	0.000	0.049	2.330	0.010
2008	0.091	3.499	0.000	0.052	2.417	0.008
2009	0.098	3.705	0.000	0.048	2.304	0.011
2010	0.100	3.765	0.000	0.047	2.296	0.011
2011	0.102	3.820	0.000	0.041	2.114	0.017
2012	0.103	3.849	0.000	0.035	1.947	0.026
2013	0.102	3.832	0.000	0.032	1.859	0.032
2014	0.105	3.883	0.000	0.032	1.863	0.031
2015	0.103	3.843	0.000	0.036	1.972	0.024
2016	0.107	3.939	0.000	0.032	1.843	0.033
2017	0.104	3.859	0.000	0.031	1.823	0.034
2018	0.106	3.912	0.000	0.032	1.861	0.031
2019	0.110	4.016	0.000	0.031	1.821	0.034

To determine the optimal spatial metrology model, LR and Wald tests are conducted in sequence. Table shows the test outcomes.

The LR-SDM-SAR and LR-SDM-SEM tests progress when there is a 5% significance level (Table 6), evincing that SDM is more appropriate. Wald's tests proceed when there is a 10% significance level, which further manifests that SDM precedes spatial error model (SEM) and spatial autoregressive model (SAR). At 10% significance level, the LR-Both-Ind test reveals that the two-way fixed model is superior to the urban fixed model. Therefore, the bidirectional fixed SDM is optimal.

Table 5. Spatial measurement model selection test

Type	Result	P
LR-Both-Ind test	27.26	0.0024
LR-Both-Time test	711.58	0.0000
LR-SDM-SAR test	22.40	0.0022
LR-SDM-SEM test	19.41	0.0070
Wald-SDM-SAR test	4.27	0.0389
Wald-SDM-SEM test	3.16	0.0755

Using LR test, the final spatial model is determined as the spatial Dubin bidirectional fixed effects model, and the spatial regression analysis is conducted to obtain the final regression outcomes (Table 6). Table 6 shows that, under the economic matrix, the spatial autocorrelation factor is -0.476, and the conclusion is obvious at 5% significance level. DE has a spatial effect on CE. The factor of DE under economic weight is -0.378, and it is obvious at 5% significance level. When the economic level of two districts is more approximate, it can promote the decrease in CE more effectively. The study speculated that it would be easier to carry out technological exchanges and cooperation of DE in the two places with relatively close economies, thus enabling the development of LC technologies within two districts at a higher level, promoting the efficient use of carbon energy and curbing total CE.

Table 6. The regression results of the spatial Dubin model

Variable	Result
Spa-rho	-0.476** (-2.27)
Dige	-0.095** (-2.52)
W × Dige	-0.378** (-2.07)
Direct effect	-0.086** (-2.13)
Indirect effect	-0.238* (-1.75)
Total effect	-0.325*** (-2.62)
Control variable	Yes
City	Yes
Year	Yes
R2	0.789
Obs	510
Log-L	932.97

Note: ***, **, and * mean obvious at 1%, 5%, and 10% significance levels, respectively. The value of z is in brackets.

To deeply analyze the spatial spillover effect of DE on CE, we conduct regression of spillover effect of DE on CE. Table 6 shows the results. Both the direct and indirect effects of DE on CE and the total factor are negative and obvious at 5%, 10%, and 1% significance levels. It manifests that when DE in this district continues to develop, the application of various modern technologies can effectively restrain CE. Meanwhile, with the constant improvement in the level of DE in neighboring areas, LC technologies in the two places can be fully cooperated and exchanged, thus promoting the rapid development of LC technologies in this district, further enhancing the inhibition influence of DE on CE. Therefore, hypothesis 3 holds true.

5.3. Homogeneity Test

Owing to the obvious differences in Chinese regional economic levels, we conduct heterogeneity test according to the division of national administrative regions to understand whether DE has regional differences in CE in different areas and at different levels of DE development. The districts are mainly divided as eastern, central, western, and northeastern. Table 7 shows the final regression results.

Table 7. Heterogeneity regression results table

Variable	Eastern region	Central region	Western region	Northeast region
Dige	-0.197*** (-6.87)	-0.123*** (-2.77)	-0.160*** (-3.64)	-0.129** (0.015)
Control variable	Yes	Yes	Yes	Yes
City	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
R2	0.940	0.932	0.910	0.969
Obs	510	510	510	510

Note: ***, **, and * mean obvious at 1%, 5%, and 10% significance levels, respectively. The value of z is in brackets.

In Table 7, we observe that DE has curbed CE in different areas, indicating that DE in all regions of China has achieved a certain level of development at the present stage. However, owing to the difference of regional economy, the inhibition impart of DE on CE is still deviated. In the eastern district, due to the high economic progress, the level of DE of the cities is relatively high, and the technical exchange is more frequent. Therefore, DE has the strongest inhibition influence on CE. In the western district, due to the strong support of national policies, various big data pilots represented by Guizhou have been developing rapidly, which makes the environmental dividends of DE in the western area more prominent.

5.4 Robust Test

To verify whether the regression results are stable, the following methods are used for robustness test: (1) Replace the space weight matrix. Considering that the choice of spatial weight matrix will contribute to differences in results, we select geo-population matrix for robustness test. The regression results show that the regression coefficient is still significant at 1% significance level and the coefficient of DE is also obvious under the geographic-population matrix (Table 8). The conclusion is still obvious after the replacement of the weight matrix, manifesting that it is robust. (2) Replace explained variables. To guarantee robust regression results, the calculation of CE has been replaced. Table 8 displays the regression results, where the spatial autocorrelation coefficient and the coefficient of DE on CE are still noteworthy under the economic matrix.

Table 8. Robustness test result table

Variable	Replace explained variables	Replace the space weight matrix
Spa-rho	-0.525*** (-2.68)	-0.095** (-2.54)
Dige	-0.083** (-2.57)	-0.350* (-1.85)
W ×Dige	-0.513*** (-3.24)	-0.651*** (-2.98)
City	Yes	Yes
Year	Yes	Yes
Obs	510	510

Note: ***, **, and * mean obvious at 1%, 5%, and 10% significance levels, respectively. The value of z is in brackets.

6. CONCLUSION

We used provincial panel data from 30 provinces from 2003 to 2019 to explore the influence of DE on CE. The study probes the influencing factor of DE on CE from multiple perspectives using fixed-effect, dynamic threshold, and spatial Dubin models and draws the following primary conclusions: First, the influence of DE on CE manifests an overturned U-shaped nonlinear relationship. With the continuous progress of DE, the effect of DE on the environment is gradually observed, which can efficaciously curb the total CE of cities. Meanwhile, the heterogeneity test results show that the effect of DE on CE is obvious in the east, central, west, and northeast districts; however, it varies owing to the various development levels of DE in different areas. Second, the influence of DE on CE has obvious spatial spillover effect, in which the development of local DE can effectively facilitate the decrease in CE in the district, and the improvement in the level of DE of neighboring cities can also facilitate the decrease in CE in the district. To verify the robustness of the results, we carried out spatial matrix replacement and explained variable replacement that indicate robust results.

Based on the above results, we recommend the following policy suggestions: First, policymakers should increase investment and support to the related industries of the DE, promote the construction of various infrastructure of DE, provide modern technical support to enhance energy supply, use modern technology to provide clean and efficient low-carbon energy, and constantly improve modern energy structure system. Finally, the spatial spillover impact of DE should be fully considered. Governments at all levels should actively enhance communication and consociation of DE, reduce the digital divide in various areas, effectively improve the overall planning capacity of energy arrangements in various regions using DE, and facilitate the continuous progress of the modernization of our energy structure.

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