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Assessing the Role of the Digital Economy on Carbon Emissions: New Evidence Based on the Spatial Durbin Model

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Abstract: With the advancement of industrialization, the problem of global warming is becoming increasingly serious. In order to reduce greenhouse gas emissions, China has proposed the goals of "Peak carbon dioxide emissions" and "Carbon neutrality". Meanwhile, under the background of computer technology, digital economy gradually takes shape, and it affects all aspects of society. In particular, it provides impetus for economic growth. While promoting economic innovation and development, whether the digital economy can reduce carbon emissions in China is worthy of in-depth research. However, it is rarely studied in the existing literature. In this paper, 261 samples were selected from the municipal level, covering the period from 2011 to 2017. Considering the possible influence of space, we construct a spatial Durbin model to explore the relationship between the digital economy and carbon emissions. We found that the digital economy can mitigate carbon emissions both locally and in neighboring areas. In addition, the digital economy has a bearing on carbon emissions which varies in different regions. Research conclusions provide useful policy implications for better promoting the development of the digital economy and helping to achieve the "dual carbon" target.

Keywords: digital economy; carbon emissions; spatial Durbin model; spatial spillover effects

JEL Classification: B23; C23

1. Introduction

Since the Industrial Revolution, the increase in productivity has led to an increasing consumption of natural resources, and various large-scale production activities have also led to a large number of greenhouse gas emissions, causing serious global warming problems. In this context, countries have introduced policies to reduce greenhouse gas emissions. In order to solve the problem of global warming, China has also proposed "peak carbon dioxide emissions" and "carbon neutrality" goals.

The digital economy is a new economic structure born from the quick advancement of computer technology. However, there is no authoritative statement on the connotation of digital economy at present, scholars understand the digital economy from different angles. The most recognized definition of digital economy is the initiative proposed by the Hangzhou G20 Summit 2016: the digital economy contains a series of economic activities, its production factor is digital knowledge and information, the carrier is modern information network, and the core driving force is the use of information and communication technology to improve efficiency and optimize economic structure.

After the advent of the digital economy, many scholars (Deng & Zhang, 2022; Li & Zhou, 2021; Guo et al., 2022; Wu et al., 2021) have studied the impact of the digital economy on environmental quality in detail, and the results of the research have consistently shown that the development of the digital economy helps improve environmental quality. Since the development of the digital economy can effectively improve environmental quality, the digital economy can exert the same effect for carbon emissions? In addition, when studying the relationship between things, it is one-sided to consider only the causal relationship between two variables, and the spatial correlation between individuals should not be ignored. With the development and improvement of econometric models, spatial metrology has been widely used in the study of economic problems. Among them, the spatial Durbin model introduces the spatial lag term of explanatory variables on the basis of the spatial lag model, and can be transformed into other models when some constraints are made on the parameters.

Based on this question, this article conducts research. We found that the development of the digital economy can relieve urban CO2 emissions when spatial spillover effects were considered. This paper provides new perspectives and ideas for achieving green and low carbon development and improving global warming, and the role of the digital economy should be fully exerted in future carbon emission reduction work.

2. Theoretical Part

2.1. Literature Review

Studies already conducted on how the digital economy affects carbon emissions can be roughly divided into three groups. According to certain research, the growth of the digital economy results in higher carbon emissions. Some scholars believe that the rapid development of the ICT industry leads to excessive consumption of electricity, which in turn drives an increase in carbon emissions (Salahuddin & Alam, 2015). Utilizing data from the top 10 countries in the world in 2019, some studies have concluded that digitalization does not support the growth of a green and energy-efficient economy, indicating that the pace of digital economy growth must be constrained in order to achieve the global sustainable development goals (Shvakov & Petrova, 2019).

According to some studies, the growth of the digital economy will contribute to the decrease of carbon emissions. Some studies have shown that digital technology can increase labor productivity, facilitate the effective allocation of resources, and support the transition of high-carbon industries to low-carbon ones (Wu & Ren, 2021). Wu Yin proposed at the Bi-Carbon Strategy and Energy Digitalization Forum held in October 2021 that digital technology can interconnect various energy systems based on electricity, optimize the energy supply system, and reduce direct carbon emissions in the terminal sector, thereby reducing carbon dioxide emissions. The development of artificial intelligence, according to Jiang Yan's argument at the forum "Digital Technology Empowers Green and Low-Carbon Development of the Industry," can support the growth of clean energy, reduce carbon emissions throughout the supply chain, and intelligently monitor inefficient production capacity. Shobande believes that in the long run, increased Internet penetration will significantly reduce carbon emissions (Shobande, 2021). Bhujabal believes that increasing investment in ICT infrastructure also has a significant effect on reducing carbon emissions (Bhujabal et al., 2021). The relationship between the digital economy and carbon emissions from the provincial level was studied using data from 2011 to 2018, and the findings indicated that the intensity of carbon emissions will decrease as the digital economy develops (Xie, 2022). When researching the influence of the energy structure on carbon emissions, Li Y included the digital economy as a moderating variable. The findings revealed that as the amount of digital economy growth increases, the energy structure's inhibitory effect on carbon emissions becomes stronger (Li et al., 2021). Xu used the spatial Durbin model for the first time to study the relationship between the two, and the results show that with the development of the digital economy, the carbon emissions of both local and neighboring places will decrease (Xu et al., 2022).

In addition, Li X. introduced the digital economy as a technological progress in the Solow growth model, performed fixed-effect regression based on global panel data from 190 countries. They discovered a nonlinear association between carbon dioxide emissions and the digital economy that is structured like an inverted U. At the beginning of digitalization, due to increased productivity, enterprises produce more goods, thereby releasing more carbon dioxide; When the level of digitalization is high, the amount of carbon dioxide processed is greater than the emission of carbon dioxide. Currently, businesses' production levels tend to be stable, and technological advancement helps the economy develop sustainably (Li et al.,2021).

In conclusion, numerous academics have assessed the state of the digital economy, and despite the lack of a standardized and cohesive indicator system, it is clear that the indicator dimension is constantly developing. However, few publications at this point make the growth of the digital economy and carbon emissions their primary study topics, and there are very few discussions on the relationship between the two, and they are basically qualitative, lacking the support of empirical models. Additionally, both quantitative research and practical testing rarely take into account the spatial association between the digital economy and carbon emissions, and simple panel regression estimation coefficients may not accurately reflect the magnitude of the effect between variables, so this article uses the spatial Durbin model for research.

2.2. Theoretical Analysis and Research Hypotheses

Companies can engage in a variety of digital economic activities without equity linkage since the digital economy exhibits the traits of a "participant economy", which also leads to its important role in reducing carbon emissions from the entire business activity (Li Y. et al., 2021). By enabling consumers and even the upstream and downstream entities of the entire supply chain to participate, the digital platform of the enterprise reduces the carbon emissions of the enterprise, thereby achieving carbon emission reduction in the entire business process. Online shopping, working from home, and online education also significantly reduce people's travel.

Additionally, as the size of the digital economy continues to grow, the digital economy has replaced many traditional economies, and the optimization of the power system and energy structure of traditional industries through digital technology will help reduce the carbon emissions of the entire society. The transition from manufacturing to services will significantly reduce society's reliance on fossil fuels, which is another essential step toward reducing carbon emissions. The digital economy also plays a significant role in fostering this improvement in industrial structure. Overall, the digital economy can drive the achievement of the "dual carbon" target and promote the green development of society. Therefore, the first hypothesis of this paper is proposed: carbon emissions are being hampered by the growth of the digital economy.

In general, economic activities between neighboring regions will affect each other, and digital technologies and emission reduction technologies are easier to circulate. In addition, the digital economy can break through traditional regional boundaries by making use of the spread of the Internet. The cost of information transmission and processing has significantly decreased with the rapid growth of digital technologies like the Internet, big data, and cloud computing, particularly under the effect of Moore's law, enhancing the mobility of data. The properties of the digital economy allow for the reduction of local carbon emissions while hindering the growth of nearby regions, which is sometimes referred to as a positive externality of the digital economy.

Therefore, this study creates a spatial econometric model for research, taking into account the fact that the spatial spillover effect of the digital economy cannot be ignored, while examining the influence of the digital economy on carbon emissions. So, the second hypothesis is put forward: the digital economy can inhibit the carbon emissions of adjacent areas through spatial spillover.

3. Methodology

3.1. Model Specification

In order to measure the strength of the relationship between the units in the space, the following matrix is constructed, where w_{ij} indicates the influence degree of individual i on individual j in the space:

$$W = \begin{bmatrix} 0 & w_{12} & \cdots & w_{1n} \\ w_{21} & 0 & \cdots & w_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ w_{n1} & w_{n2} & \cdots & 0 \end{bmatrix} \tag{1}$$

As there are many types of spatial weight matrix, this paper refers to the relevant research, considering the simplicity of matrix construction, and selects the following two most commonly used for research.

The rules for constructing the adjacency weight matrix are as follows:

$$w_{ij} = \begin{cases} 1, & \text{Spatial units i and j have a common boundary} \\ 0, & \text{Spatial elements i and j have no common boundary, or } i = j \end{cases}$$

The geographical distance weight matrix assumes that the spatial effect is negatively correlated with the unit distance, and the form is as follows:

$$w_{ij} = \frac{1}{d_{ij}} \left(d_{ij} \text{ represents the geographic center distance of the spatial units } i \text{ and } j\right)$$

Spatial autocorrelation test is the premise of spatial econometric analysis. According to the first law of Geography: Everything is related and the closer the distance, the closer the relationship will be. When examining the relationship between the two variables, we should consider the interaction between adjacent areas, that is, spatial effect. At present, the commonly used indicators to investigate the spatial autocorrelation of data are Moran index *I* and Geary index *C*. In this paper, Moran index is used to analyze the global spatial autocorrelation.

The formula for the global Moran index is as follows:

$$I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(y_i-\bar{y})(y_j-\bar{y})}{S^2 \sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}}, \tag{2}$$

$$S^2 = \sum_{i=1}^{n}(y_i - \bar{y})^2/n,\ \bar{y} = \sum_{i=1}^{n} y_i/n,\ w_{ij} \tag{3}$$

is an element in the spatial weight matrix, as described above, y_i represents the value of the ith sample on the variable y, y_j represents the value of the *j*th sample on the variable *y*, and *n* represents the sample size.

The global Moran Index *I* has a range of $-1 \leq I \leq 1$, which describes the overall distribution of variables and determines whether they will agglomerate in space. When *I* is less than 0, it indicates that there is a spatial negative correlation between the variable Y, implying that there is a large difference between adjacent elements; When *I* is more than 0, it indicates a positive spatial correlation, implying that the values of adjacent cells on variable Y are very close, and the high value (or low value) regions are clustered together; When *I* is equal to 0, the variable Y is randomly distributed.

When estimating the effect of the development of the digital economy on carbon emission, the regression coefficient may be inaccurate if the conventional panel model is used directly due to the clear spatial correlation between the level of development of the digital economy and the level of carbon emission in cities. Therefore, it is necessary to establish a spatial econometric model.

In order to select the appropriate model, this paper has carried out a series of tests including LM test, Hausman test, LR test, and Wald test (Because of limited space, test results are omitted from the article). Finally, the SDM model was selected for empirical research, and the model settings were as follows.

$$\ln CO2_{it} = \rho \sum_{j=1, j\neq i}^{n} W_{ij} \ln CO2_{it} + \beta_1 \ln X_{it} + \gamma_1 \sum_{j=1}^{n} W_{ij} \ln X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{4}$$

The difference between the spatial Durbin model and the ordinary panel model is that the spatial lag term of the explanatory variable is introduced as the explanatory variable, that is, the first term at the right end of the above formula. $\ln CO2_{it}$ represents local CO2 emissions, $\sum_{j=1, j\neq i}^{n} W_{ij} \ln CO2_{it}$ indicates the CO2 emissions of neighboring areas, and the coefficient ρ reflects the impact of CO2 emissions from neighboring areas on local CO2 emissions, also known as spatial spillover. In addition, the spatial Durbin model also introduces the spatial lag term of the explanatory variable (which is an important difference between the spatial Durbin model and the spatial lag model), which is the third at the right end of the above equation, which is to measure the impact of the development of the digital economy and other control variables on local CO2 emissions in neighboring areas.

$CO2_{it}$ represents the city's level of carbon emissions; X_{it} denotes explanatory variables, including core explanatory variables and control variables; ρ is the spatial lag regression coefficient of the dependent variable, which depicts the relationship between regional carbon emissions and those of nearby locations; β_1 is the regression coefficient for the explanatory variables; γ_1 is the spatial lag regression coefficient of the explanatory variable, which indicates the effect of the development of the local digital economy on the carbon emissions of neighboring areas; μ_i indicates regional effects; λ_t means the time effect; ε_{it} is a random perturbation term.

3.2. Variable Selection

In this paper, the carbon dioxide emission (million tons) is selected as a dependent variable and is expressed by lnco2. The measurement method is the apparent emission accounting method. Urban carbon emissions are calculated by adding the carbon emissions of the counties under their jurisdiction.

Table 1. Evaluation index system of digital economy development

Primary indicator	Secondary indicator	Tertiary indicator	Indicator attribute
Digital economy development index	Internet penetration rate	Number of Internet broadband access users per 100 people	+
	Number of internet-related employees	Proportion of information transmission computer service and software industry in employees of urban units	+
	Internet-related outputs	Per capita telecom business income (10,000 RMB)	+
	Number of mobile Internet users	Number of mobile phone subscribers per 100 people	+
	Inclusive development of digital finance	China Digital Financial Inclusion Index	+

The Digital Economy Development Index is the explanatory variable. Five indicators were chosen in accordance with the index system created by Zhao Tao to assess the state of the urban digital economy (Zhao et al., 2020), and the entropy weight method was used to synthesize the digital economy development index (DIGE). Table 1 displays the indexing methodology for the digital economy development index.

In this paper, six control variables are selected with reference to the relevant literature on the factors that influence carbon emissions according to Table 2.

Table 2. Description of the control variables

	Primary indicator	Secondary indicator
Economic level	Level of economic development	Per capita GDP（gdpp）
Demographic level	Population size	Resident population (popu)
Technical level	Technological innovation	Patent authorization (pat)
Others	Industrial structure	Industrial structure supererogation (indu)
	Urbanization level	Urbanization rate (city)
	Investment in fixed assets	Amount of investment in fixed assets (fai)

3.3. Data Sources

Data from 261 Chinese prefecture-level cities between the years of 2011 and 2017 are used in this study, and some missing data are filled up using linear interpolation. Additionally, every statistic in the empirical portion is logarithmic, with the exception of the digital economy development index. The Peking University's Digital Finance Research Center provided the digital inclusive finance index, and the carbon emission data is derived from the county-level carbon dioxide emissions measured by Chen et al. (2020). The total carbon emissions of the counties under their authority are added to determine urban carbon emissions. The data of other indicators come from the urban statistical yearbook, wind database, EPS database, urban statistical bureaus, and Statistical Bulletins.

4. Results

4.1. Spatial Autocorrelation Test

Table 3. Results of the Global Moran Index

Year	Moran Index			
	Digital economy Development index		Carbon dioxide emissions	
	The adjacency weight matrix	The geographic distance weights matrix	The adjacency weight matrix	The geographic distance weights matrix
2011	0.278***	0.077***	0.286***	0.080***
2012	0.252***	0.069***	0.284***	0.079***
2013	0.210***	0.057***	0.274***	0.075***
2014	0.206***	0.052***	0.270***	0.074***
2015	0.194***	0.050***	0.284***	0.079***
2016	0.186***	0.048***	0.282***	0.079***
2017	0.197***	0.051***	0.263***	0.072***

Note: ***, ** and * indicate a level of significance of 1%, 5%, and 10%, and the following table is the same.

Before estimating the spatial econometric model, calculate the Moran index to test whether there is spatial correlation. Table 3 shows that under the two spatial weight matrices, the Moran index values (I) of the digital economy development index and carbon dioxide emissions from 2011 to 2017 are significantly positive. This demonstrates the relationship between urban carbon emissions and the development of their digital economies as a spatial agglomeration phenomenon in China. It implies that the level of local carbon emissions and the development of the local digital economy may have an impact on areas nearby, and it is initially shown that there is a spatial spillover effect.

4.2. Basic Regression

Table 4 demonstrates that the impact of the digital economy development index on CO2 emissions under both spatial weighting matrices is negative, at least with a significance level of at least 5% regardless of whether control variables are added, and the coefficient difference is small, indicating that the level of carbon emissions in cities can be significantly reduced by the development of the digital economy. Taking the adjacency weight matrix as an example, with the addition of control variables (model 2), there will be a 0.117% decrease in the city's carbon dioxide emissions for every unit increase in the digital economic development index. In addition, urban carbon emissions' spatial lag coefficient (rho) is noticeably positive, indicating that in China, there is a large spatial spillover impact on urban carbon emissions, and local carbon emissions have a positive impact on neighboring areas, which is confirmed by the Moran index calculated previously. The spatial lag coefficient of the digital economy development index is significantly negative, demonstrating how the digital economy has had a positive knock-on impact and decreased carbon emissions in nearby places. In this part, only the control variables with significant spatial lag coefficients are retained, and it can be found that under the two spatial weight matrices, the fixed asset investment (lnfai) of neighboring areas has a significant inhibitory effect on local carbon emissions (with coefficients of -0.021 and -0.166). Technological innovation (lnpat) in neighboring areas exacerbates local carbon emissions (with coefficients of 0.029 and 0.154).

Table 4. Results of basic regression

Explanatory variable	The adjacency weight matrix				The geographic distance weights matrix			
	Model 1		Model 2		Model 3		Model 4	
	x	W×x	x	W×x	x	W×x	x	W×x
dige	-0.150*** (0.049)	-0.287*** (0.089)	-0.117** (0.047)	-0.274*** (0.090)	-0.116** (0.050)	-1.275** (0.590)	-0.112** (0.051)	-3.070*** (0.673)
lnfai			0.030*** (0.006)	-0.021** (0.009)			0.037*** (0.006)	-0.166*** (0.042)
lnpat			0.001 (0.004)	0.029*** (0.006)			-0.001 (0.004)	0.154*** (0.027)
rho	0.505*** (0.023)		0.485*** (0.023)		2.440*** (0.047)		0.884*** (0.042)	
control variables	NO		YES		NO		YES	
time fixed	YES		YES		YES		YES	
individual fixed	YES		YES		YES		YES	
years	7		7		7		7	
cities	261		261		261		261	
R^2	0.018		0.024		0.034		0.041	
LogL	3,454.894		3,548.497		3,431.615		3,464.070	

Note: ***, ** and * indicate the level of significance of 1%, 5%, and 10%. What is reported in brackets in the table is the robust standard error.

4.3. Effect Decomposition

Due to the spatial lag term's feedback effect, that is, the coefficient of spatial lag term (rho) of the explained variable is significantly not 0, the coefficient value of spatial Durbin model in the benchmark regression cannot accurately reflect the degree of real influence between variables (Nan et al., 2022). Referring to the partial differential method of the spatial regression model proposed by Lesage and Pace (2009, p. 513–551), the direct effect and indirect effect are separated from the total effect of the spatial Durbin model to reduce the error in the estimation of coefficients, as shown in Table 5.

The results show that the direct effect of digital economy development on urban carbon emissions is significantly negative, specifically, when the local digital economy development index increases by 1 unit, there will be a 0.163% decrease in the local economy's carbon emissions. The development of the local digital economy has a spillover impact on nearby areas, reducing their carbon emissions, as shown by the indirect effect, which is also notably negative.

Table 5. Results of effect decomposition

Explanatory variable	The adjacency weight matrix		
	Direct effect	Indirect effect	Total effect
dige	-0.163*** (0.052)	-0.594*** (0.157)	-0.757*** (0.185)
lngdpp	0.090*** (0.014)	-0.065* (0.035)	0.025 (0.037)
lnindu	0.246** (0.113)	-0.319 (0.301)	-0.073 (0.329)
lnpopu	0.117*** (0.028)	0.117 (0.100)	0.233** (0.115)
lncity	0.077*** (0.018)	-0.101** (0.048)	-0.024 (0.058)
lnfai	0.029*** (0.006)	-0.013 (0.013)	0.016 (0.014)
lnpat	0.006 (0.004)	0.053*** (0.010)	0.058*** (0.011)
time fixed	YES		
individual fixed	YES		
years	7		
cities	261		
R^2	0.018		
LogL	3,548.497		

Note: ***, ** and * indicate the level of significance of 1%, 5%, and 10%. What is reported in brackets in the table is the robust standard error.

4.4. Robustness Test

By gradually adding the control variables and substituting per capita CO2 emissions for the explanatory variables, we discovered that the key explanatory variables' and lagging terms' coefficient estimates are still significant, their signs have not changed, and their fluctuation range is not very high, so the model is basically robust. (Because of space limitations, table results are not displayed.)

4.5. Spatial Heterogeneity Analysis

Taking into account the spatial variability of the influence of the digital economy's development on urban carbon emissions, we divide all cities into three regions: the east, the centre, and the west for regression. Due to the spatial lag term's feedback effect, the regression outcomes are displayed in Table 6 along with the effect's ongoing decomposition.

In the eastern region, the development of the digital economy has a significant inhibitory effect on local and adjacent carbon emissions. It may be that the Internet and computer technology in the eastern region are quite mature, with a high degree of digitization, and the digital technology is deeply integrated with the real economy. Economic activities are more energy-saving and environmentally friendly. The developed digital technology also promotes the development of new energy. Therefore, the effect of the digital economy on reducing carbon emissions is stronger. In the central region, the development of the digital economy has no obvious effect in alleviating local carbon emissions, but it has reduced the carbon emissions of neighboring regions. The reason may be that the development of digital economy in the central region is later than that in the eastern region, the Internet and digitization level are not high, and the infrastructure is not sophisticated, so the effect of carbon emission reduction is not as obvious as that in the eastern region. In the western region, the development of the digital economy has no significant impact on local and adjacent carbon emissions. Our guess is that it is because the development of the digital economy in the western region is still in its primary stage, the degree of integration with the real economy is low, and the digital technology is not advanced enough, so it cannot play a significant role in reducing carbon emissions.

Table 6. Results of heterogeneity analysis

Digital economy development index	Eastern Region	Central Region	Western Region
Direct effect	-0.344*** (0.084)	-0.001 (0.083)	0.039 (0.097)
Indirect effect	-0.425* (0.252)	-1.285*** (0.264)	0.195 (0.204)
Total effect	-0.769** (0.297)	-1.285*** (0.312)	0.234 (0.261)
control variables	YES	YES	YES
time fixed	YES	YES	YES
individual fixed	YES	YES	YES
years	7	7	7
cities	101	100	60
R^2	0.039	0.003	0.190
LogL	1,418.265	1,521.658	812.362

Note: ***, ** and * indicate the level of significance of 1%, 5%, and 10%. What is reported in brackets in the table is the robust standard error.

5. Conclusions and Suggestions

5.1. Conclusions

We build a spatial Durbin model for empirical research to investigate the effects of the rise of the digital economy on carbon emissions. Three conclusions are reached as follows:

First, the expansion of the digital economy continues to have a sizable inhibitory effect on urban carbon emissions even after accounting for the spatial spillover effects of the digital economy and carbon emissions, which agrees with the findings of other academics' empirical studies employing regular panels. To ensure the reliability of the research results, robustness tests were carried out. After six control variables were introduced in turn and the explained variables were replaced by per capita carbon dioxide emissions, the findings demonstrated that the lag term and the main explanatory variable coefficient estimates were still significant, the symbols did not change, and the fluctuation range was small. The robustness test passed.

Second, considering the feedback effect of the spatial lag term, the partial differential method is used to decompose it. The results demonstrate that carbon emissions have been negatively impacted both directly and indirectly as the digital economy has grown. As a result, as the digital economy grows in a particular area, local carbon emissions are reduced as well as those in neighboring regions as a result of the spillover effect.

Third, all cities are divided into three regions: East, Centre and West for heterogeneity analysis. The results show that: In the eastern region, with the improvement of the level of development of the digital economy, the local and adjacent carbon emissions will be reduced. In the central region, the development of the digital economy will only reduce the carbon emissions of neighboring regions. In the western region, the development of the digital economy has no significant impact on carbon emissions.

5.2. Policy Suggestions

Based on the above research conclusions, this paper puts forward the following policy recommendations to better promote the development of the digital economy and help to achieve the "dual carbon" target:

First, the digital economy plays an important role in reducing carbon emissions which indicates we should accelerate the construction of the Internet and promote the deep integration of digital technology and economic activities. In addition, through scientific and technological innovation, we will break through a number of crucial technologies that support carbon emission reduction, vigorously develop new energy, and gradually increase the proportion of new energy.

Second, regional differences make the carbon reduction effect of digital economy diverse, which indicates it’s essential to carried out a dynamic and multiplex strategy. Especially for cities in the eastern region, continue to maintain the vitality of the digital economy and make it the technical support for regional carbon emission reduction. For the central region, we should make full use of the spillover effect of the neighboring digital economy and strengthen interregional cooperation, in order to help develop local digital technology and promote carbon emission reduction. For the western region, we should adjust the pace of digital economy development, strengthen policy guidance, and strongly support the development of digital industry, so that the digital economy can play an important role in the reduction of carbon emissions.

Conflict of interest: none

References

Bhujabal, P., Sethi, N., & Padhan, P. C. (2021). ICT, foreign direct investment and environmental pollution in major Asia Pacific countries. *Environmental Science and Pollution Research*, *28*, 42649–42669. https://doi.org/10.1007/s11356-021-13619-w

Chen, J., Gao, M., Cheng, S., Hou, W., Song, M., Liu, X., Liu, Y., & Shan, Y. (2020). County-level CO2 emissions and sequestration in China during 1997-2017. *Scientific Data*, 2020, 7(1), 391. https://doi.org/10.1038/s41597-020-00736-3

Deng, R. R., & Zhang, A. X. (2022). Research on the impact and mechanism of urban digital economy development on environmental pollution in China. *South China Journal of Economics*, (02), 18–37.

Guo, B. N., Wang, Y., & Zhang, H. (2022). Does the development of digital economy improve urban air quality: Quasi-natural experiments based on the national big data comprehensive pilot zone? *Journal of Guangdong University of Finance & Economics*, *37*(1), 58–74.

Lesage, J. P, & Pace, R. K. (2009). *Introduction to Spatial Econometrics*. *CRC Press*.

Li, G. H., & Zhou, X. L. (2021). Whether promoting the development of digital economy can improve China's environmental pollution: A quasi-natural experiment based on the "Broadband China" strategy. *Macroeconomics*, (07), 146–160.

Li, X., Liu, J., & Ni, P. (2021). The Impact of the Digital Economy on CO2 Emissions: A Theoretical and Empirical Analysis. *Sustainability*, *13*(13), 7267. https://doi.org/10.3390/su13137267

Li, Y., Yang, X. D., Ran, Q. Y., Wu, H. T., Muhammad, I., & Munir, A. (2021). Energy structure, digital economy, and carbon emissions: evidence from China. *Environmental Science and Pollution Research*, *28*(45), 64606–64629. https://doi.org/10.1007/s11356-021-15304-4

Nan, S. J., Huo, Y. C., You, W. H., & Guo, Y. W. (2022). Globalization spatial spillover effects and carbon emissions: What is the role of economic complexity? *Energy Economics*, *112*, 106184. https://doi.org/10.1016/j.eneco.2022.106184

Salahuddin, M., & Alam, K. (2015). Internet usage, electricity consumption and economic growth in Australia: A time series evidence. *Telematics and Informatics*, *32*(4), 862–878. https://doi.org/10.1016/j.tele.2015.04.011

Shobande, O. A. (2021). Decomposing the persistent and transitory effect of information and communication technology on environmental impacts assessment in Africa: Evidence from Mundlak Specification. *Sustainability*, *13*(9), 4683. https://doi.org/10.3390/su13094683

Shvakov, E. E., & Petrova, E. A. (2019). Newest trends and future scenarios for a sustainable digital economy development. In E. Popkova, & B. Sergi (Eds.), *Scientific and Technical Revolution: Yesterday, Today and Tomorrow. ISC 2019. Lecture Notes in Networks and Systems* (Vol. 129, pp. 1378–1385). Springer, Cham. https://doi.org/10.1007/978-3-030-47945-9_150

Wu, Q., & Ren, D. M. (2021). Digital economy helps green and low-carbon development. *View Financial (Fortune)*, (11), 16–17.

Wu, Y. J., Luo, C. X., & Luo, L. Q. (2021). The impact of digital economy development on sulphur dioxide emissions: An empirical evidence based on provincial panel data. *Journal of Wuhan Polytechnic*, *20*(1), 82–88.

Xie, Y. F. (2022). The effect and mechanism of digital economy on regional carbon emission intensity. *Contemporary Economic Management*, 1–16.

Xu, W. X., Zhou, J. P., & Liu, C. J. (2022). Spatial effects of digital economy development on urban carbon emissions. *Geographical Research*, *41*(1), 111–129.

Zhao, T., Zhang, Z., & Liang, S. K. (2020). Digital economy, entrepreneurial activity and high-quality development: Empirical evidence from Chinese cities. *Management World*, *36*(10), 65–76.