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SPATIAL LINKAGES BETWEEN DIGITAL ECONOMY AND CARBON REDUCTION UNDER DUAL CARBON GOALS

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Abstract. Since announcing its "dual carbon" goals, China has made reducing carbon emissions a top priority. This study utilizes panel data from 285 cities in China, from 2011–2021, to systematically examine the relationship between the digital economy and urban carbon output. It aims to identify their relationship by introducing SDM and DID model. The findings are as follows: (1) Improving the digital economy is essential to significantly lowering carbon output. These benchmark regression results have passed robustness tests. (2) The SDM model results show that the development of the digital economy significantly reduces both total and direct carbon emissions in local cities, and there is a significant spatial spillover effect. (3) The digital economy's impact on carbon reduction varies greatly by regional distribution and city size, exhibiting significant heterogeneity.

Keywords: digital economy, carbon emissions reduction, DID, SDM, PSM-DID.

JEL Classification: M41, C83, L20.

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1. Introduction

Ever since the "dual carbon goal" was announced, concerted efforts have been devoted to reducing carbon emissions, prompting extensive academic research. Scholars have employed bibliometric methods to achieve a thorough analysis and summary of China's carbon emissions issues, yielding significant findings. Regarding carbon emissions trading in China, researchers have conducted comprehensive studies using methods such as difference-in-differences (Sun et al., 2021; Yang et al., 2020), quota sampling (Wu et al., 2019), and documentary research (Wang et al., 2019). Studies on carbon emissions have primarily focused on provincial and municipal levels. Tian et al. (2016) investigated the carbon output of the agricultural sector in Hunan Province using multiple regression and decoupling analysis (Tian et al., 2016), while Tseng (2019) analyzed carbon emission influencing factors in Inner Mongolia using the LMDI (Tseng, 2019). At the municipal level, Wang et al. (2013) measured Shanghai's carbon emissions using the emission factor method, and Yang et al. (2017) assessed Xi'an's carbon emissions from an urban transportation development perspective. Luo et al. (2019) analyzed Wuhan's carbon emissions using the carbon emission decomposition method. Researchers have also explored factors affecting carbon emissions, focusing on energy structure changes

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(Wang et al., 2016), population mobility (Wu et al., 2021), and higher education development (Zhu et al., 2021).

The digital economy, being a novel economic form, effectively encourages high-quality urban development. It also demonstrates some environmental benefits (Yin & Yu, 2022). For instance, Yu and Zhu (2022) incorporated their mediation model with the geographically weighted regression, found that the digital economy helps reduce energy intensity, thereby lowering CO_2 output (Yu & Zhu, 2022). However, there are also divergent academic opinions on this issue. Wu et al. (2021) suggested that digital technology elevates carbon emission efficiency, whereas Islam et al. (2024) argued that it may not lead to a reduction in total carbon emissions. Results can vary even when studies are conducted in the same location (Chen et al., 2020; Zhang et al., 2021).

To offer theoretical backing for the effects of carbon emissions brought about by the digital economy, extensive academic discussions have been carried out on factors affecting carbon emissions. Besides, great attention has also been given to the environmental benefits associated with the digital economy. However, existing studies still provide insufficient reliable evidence. On the one hand, existing research mostly focuses on a single region or city, lacking a systematic analysis of the heterogeneity of different regions across the country. On the other hand, existing research lacks multidimensional examination of the interactions between cities. This study aims to fill these research gaps by addressing the following questions: How are carbon emissions in the relevant cities affected by establishing big data pilot zones? Does this relationship hold when spatial effects are considered? What spatial spillover effects can be identified?

This article may provide three marginal contributions: First, in the field of carbon emission accounting, it distinguishes urban carbon emissions into four categories – total, direct, indirect, and other carbon emissions – rather than relying solely on traditional accounting methods based on fossil fuel consumption or energy activities. Second, the study leverages external shocks – such as “smart cities”, “Broadband China”, “clean energy demonstration provinces” to rigorously verify the digital economy’s impact. Third, the article examines spatial spillover boundary effects by constructing spatial threshold matrices. It analyzes how pilot zone policies affect local carbon emissions and evaluates their broader impact on other cities at varying distances. In summary, this study provides new perspectives and practical pathways for achieving carbon neutrality.

Following this introduction, Section 2 establishes the theoretical foundation by reviewing policy backgrounds and formulating research hypotheses. Section 3 elaborates on the methodology, and data processing procedures. Section 4 visualizes the spatial distribution patterns of urban carbon emission. Section 5 further spatial analyses using the Spatial Durbin Model. Finally, Section 6 concludes with policy recommendations tailored to spatial governance and proposes future research directions.

2. Policy background and research hypothesis

2.1. Policy background

As information technology becomes increasingly integrated into society and the economy, data has become the most dynamic innovation element in the new industrial revolution. Data is not only a fundamental and strategic resource but also a new boost to economy in the modern era. The role of big data in national governance, economic development, and social life has grown increasingly significant. To develop the digital economy at a faster pace, big data development strategies have been rolled out in major industrialized countries around the world.

For instance, in 2012, the "Big Data Research and Strategic Plan"[1] was announced in the United States, vigorously promoting the development of cutting-edge core technologies in big data. In 2013, the United Kingdom and France released strategic plans such as "Seizing the Data Opportunity: A Strategy for UK Data Capability"[2] and the "Digital Roadmap ".[3] In December 2019, the U.S. White House released the "Federal Data Strategy 2020 Action Plan,"[4] aimed at strategically exploiting data. In 2020, the EU published the "European Data Strategy,"[5] aspiring to become the world's most dynamic, data-agile economy.

China's big data development strategy has been steadily advancing. In 2014, the Government Work Report mentioned "big data" for the first time. In 2015, the State Council released the "Outline of Actions for Promoting the Development of Big Data" and the "Guiding Opinions on Actively Promoting the 'Internet Plus' Campaign," emphasizing the urgency of accelerating big data deployment. Currently, the big data pilot zone construction has been authorized in two batches. 2015 saw the designation of Guizhou Province as the first batch. The second group was declared in 2016, including Inner Mongolia, Shenyang, Chongqing, Henan, Shanghai, the Pearl River Delta, and Beijing-Tianjin-Hebei. Today, China has a total of eight such pilot zones, advancing big data industries in the northeastern, western, central, and eastern regions. These zones facilitate industrial transformation, regional collaborative development, and data sharing. This approach aims to demonstrate and drive innovation in big data, foster industry growth, and enhance data sharing and utilization, thereby elevating China's big data capabilities.

2.2. Research hypothesis

2.2.1. Direct impacts

First, the digital economy, as it garnered greater importance, has improved the urban digital infrastructure, particularly through the construction of cloud computing data centers and 5G base stations. These advancements have increased the speed of information transmission, facilitated the widespread adoption of remote work, and effectively reduced carbon emissions associated with commuting (Huang et al., 2023). Second, the digital economy has elevated data to an ever more important factor of production, transforming the structure of traditional production factors (Wang & Shao, 2023). This shift has decreased reliance on labor and energy (Gan et al., 2023), positioning data as the most critical production factor in the digital era (Farboodi et al., 2019). Consequently, the allocation of production factors has become more optimized, improving resource efficiency and contributing to lower emissions. Finally, the structure of urban energy consumption has improved with the rise of the digital economy. By lowering the cost of renewable resources and boosting their market share, digital technologies have contributed to this optimization (Lyu & Liu, 2021).

H1: The development of the digital economy positively contributes to the reduction of urban carbon emissions.

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1 https://obamawhitehouse.archives.gov/blog/2012/03/29/big-data-big-deal?

2 https://assets.publishing.service.gov.uk/media/5a7bac0d40f0b638d61be312/bis-13-1250-strategy-for-uk-data-capability-v4.pdf

3 https://www.slideshare.net/slideshow/feuille-route-numrique-du-gouvernement-2013/43984125?

4 https://strategy.data.gov/assets/docs/2020-federal-data-strategy-action-plan.pdf

5 https://www.docin.com/p-2322519105.html

2.2.2. Spatial spillover effects

There is a spatial correlation between any occurrences, according to the first law of geography. The digital economy strengthens interregional economic interactions by reducing the time and space required for information transmission (Banalieva & Dhanaraj, 2019). These interactions not only promote regional economic growth and technological innovations (Hao et al., 2023), but also improve resource allocation (Ma & Zhu, 2022), which in turn impacts emission in neighboring regions. New economic geography theory upholds that in regional development, environmental spillover and knowledge spillover exhibit dual characteristics, reflecting both positive and negative spillover effects. This duality is evident in the digital economy's spillover effects on emission reduction (Zhang et al., 2022). Meanwhile, increased energy consumption has been spotted due to growing digital infrastructure in neighboring areas driven, potentially leading to resource depletion in those areas and adversely affecting their carbon emission reduction efforts.

H2: The digital economy's impact on carbon emissions exhibits a spatial spillover effect.

2.2.3. Spatial and temporal heterogeneity

According to Spatial Economics, the digital economy, through leveraging advanced technologies, say, the IoT and big data, can overcome traditional geographic and temporal restrictions, thereby altering the temporal and spatial layout of production activities. This progress can lead to new forms of spatial agglomeration of economic activities (Lange et al., 2020). However, achieving this requires continuous improvement in regional digital infrastructure and Internet technology, along with a robust economic and developmental environment (Liang & Li, 2023). In China, no city fully meets the ideal conditions for the progress of the digital economy, leading to spatial imbalances in its growth across different cities. Given the distinct variations in economic development levels, natural resources, and geographic environments across various regions of China (Manne & Richels, 1999), the geographical disparities in the emissions impact have been largely overlooked (Zhong et al., 2021).

H3: Regions with uneven digital economy development exhibit varying effects on lowering carbon output.

3. Research design

3.1. Model setting

3.1.1. Static panel modeling

If the carbon emissions in the treatment group decline significantly following the establishment of the experimental zone – and this reduction surpasses the changes in the control group over the same period – it suggests that the big data pilot zones have contributed to urban carbon reduction. Therefore, this study adopts the DID method to examine the impact of establishing big data pilot zones on urban carbon emissions.

$$\ln co_{it} = \alpha + \beta bigdata_i \times post_t + Control_{it} + \sigma_i + \tau_t + \varepsilon_{it}; \tag{1}$$

$$\ln co1_{it} = \alpha + \beta bigdata_i \times post_t + Control_{it} + \sigma_i + \tau_t + \varepsilon_{it}; \tag{2}$$

$$\ln co2_{it} = \alpha + \beta bigdata_i \times post_t + Control_{it} + \sigma_i + \tau_t + \varepsilon_{it}; \tag{3}$$

$$\ln co3_{it} = \alpha + \beta bigdata_i \times post_t + Control_{it} + \sigma_i + \tau_t + \varepsilon_{it}. \tag{4}$$

Subscripts i and t respectively represent city and year. The dependent variable $\ln co_{it}$ represents the total CO_2 and GHG output level of city i in year t. The variables $\ln co1_{it}$, $\ln co2_{it}$, and $\ln co3_{it}$ represent the direct carbon emission level, indirect carbon emission level, and other emission levels of city i in year t, respectively. The dummy variable $bigdata_i$ shows if city i belongs to a big data pilot zone, taking the value 1 if it does and 0 otherwise. The time frame before and after the big data experimental zone policy was in place is shown by the dummy variable $post_t$. The term $Control_{it}$ represents city-level control variables that could influence the urban carbon emissions level over time.

3.1.2. Spatial panel modeling

The release of the GHG, especially the CO_2, affects the local environment as well as the neighboring areas, exhibiting obvious spatial correlation. In light of this premise, an econometric model is constructed to analyze the impact on carbon emissions of digital economy development from a spatial perspective.

$$\ln co_{it} = \alpha_0 + \rho \sum_{j=1}^{N} W_{ij} \ln co_{it} + \beta X_{it} + \theta \sum_{j=1}^{N} W_{ij} X_{it} + \mu_i + \sigma_i + \varepsilon_{it}; \tag{5}$$

$$\varepsilon_{it} = \delta \sum_{j=1}^{N} W_{ij} \varepsilon_{it} + \vartheta_{it}. \tag{6}$$

W_{ij} is the spatial panel weight matrix. The spatial adjacency weight matrix is applied to the spatial Durbin model in this study. In this model, δ represents the spatial autocorrelation coefficient and ρ denotes the spatial autoregressive coefficient.

3.2. Settings of various variables

3.2.1. The explanatory variables

By dividing the scope of emission sources, Urban carbon accounting aims to avoid double counting, drawing on the guidelines from the World Resources Institute's Inventory of GHG Emissions from Enterprises. These sources are categorized into three major scopes:

Scope 1: All direct emissions that fall under an urban area are included in this scope.

Scope 2: Emissions connected to indirect energy use that take place outside of urban jurisdiction are referred to as scope 2.

Scope 3: Indirect emissions resulting from operations within the city but occurring outside its jurisdiction fall under Scope 3, which is separate from Scope 2.

The categorization, proposed and systematically defined by Kennedy and Sgouridis (2011), provides a comprehensive framework for urban carbon accounting, ensuring accurate and consistent reporting of GHG emissions.

3.2.2. Core explanatory variables

The interaction term (big data) serves as the core explanatory variable. It indicates whether a sample city i is assigned to a pilot zone at a given time t, coded as 1 if it is and 0 if it is not. The coefficient β associated with this variable represents the pilot zone policy's net effect on the city's carbon emissions. A negative coefficient suggests that the policy exerts restraining effects on carbon emission, with the coefficient's magnitude reflecting the degree of this effect. To construct the core explanatory variable, the study collects and organizes the names of the regions designated as pilot zones in 2015 and 2016 from the Chinese government website. Specifically, the Pearl River Delta region and Shenyang City have a broader influence that extends beyond their core cities to other cities within Guangdong and Liaoning provinces. Therefore, in the empirical analysis, all cities in Guangdong and Liaoning are treated as part of the treatment group.

3.2.3. Control variables

With deepening research in the academic field and relevant findings on factors affecting carbon emission intensity, this study introduces several control variables to ensure accurate results regarding the impact on emissions. Relevant variables are displayed as follows:

1. Resident Affluence extent (lnincom): Measured by the per capita income of urban residents.
2. Population Scale (lnpopu): This refers to the total sum of urban residents.
3. Environmental Pollution (poll): This variable includes industrial emissions from smoke (dust), sulfur dioxide, and wastewater. The index is calculated using the entropy method.
4. Energy Consumption Level (lnelec): This refers to the per capita consumption of electricity in the municipality.
5. Government Expenditure (gov): Measured as the ratio of general public budget expenditure to GDP.
6. Industrial Structure Advancement (indust): Represented by the proportion of the tertiary sector in GDP.
7. Fixed Asset Investment (lninvest): This variable measures the impact of per capita total fixed asset investment on carbon emission.

3.3. Data origins and processing

Based on data accessibility and completeness, this study selects 285 cities as the research subjects, covering the period from 2011 to 2021. The data are primarily from the 2012–2022 China Energy Statistical Yearbook, China Urban Statistical Yearbook, statistical yearbooks of prefecture-level cities, and statistical bulletins of prefecture-level cities. For missing values, to guarantee data completeness, the ARIMA prediction method and linear interpolation approach are used. Descriptive statistics for the variables are shown in Table 1.

Table 1. Descriptive statistics

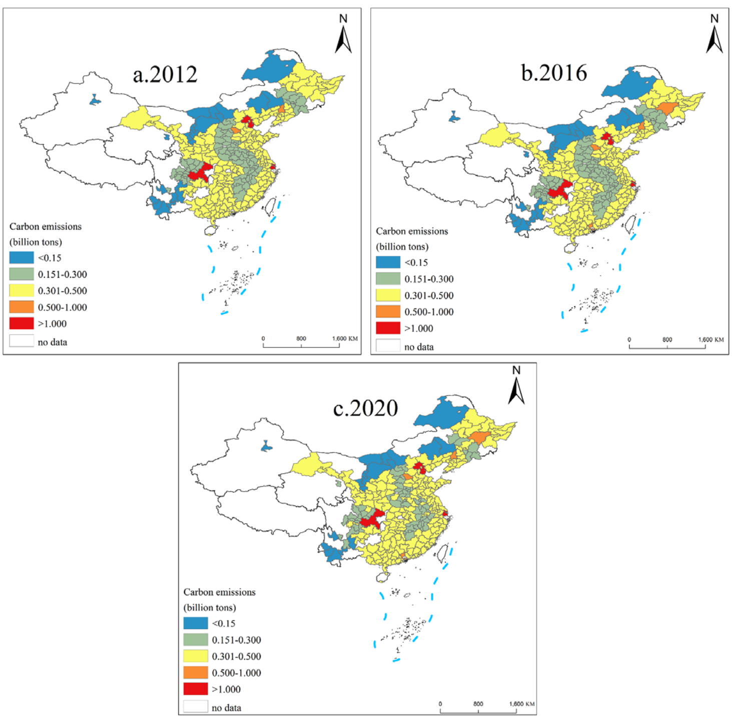
Name	Sign	N	Min	Max	Mean	Sd
Total carbon emissions	lnco	3,135	6.487	11.05	8.082	0.531
Scope 1	lnco1	3,135	6.042	10.62	7.651	0.534
Scope 2	lnco2	3,135	4.313	9.144	6.164	0.569
Scope 3	lnco3	3,135	4.447	9.389	6.451	0.567
The interaction term	bigdata	3,135	0	1	0.159	0.366
Resident affluence extent	lnincom	3,135	9.366	11.08	10.27	0.319
Population scale	lnpopu	3,135	2.970	7.227	5.900	0.676
Environmental pollution index	lnpoll	3,135	–8.587	–0.991	–2.720	0.905
Level of energy consumption	lnelec	3,135	–2.558	7.431	5.607	0.763
Government expenditure	gov	3,135	0.0439	0.613	0.203	0.0984

End of Table 1

Name	Sign	N	Min	Max	Mean	Sd
Industrial structure advancement	indust	3,135	0.144	0.717	0.425	0.0990
Fixed asset investment	lninvest	3,135	–4.061	3.049	1.321	0.841

4. Characteristics of spatial distribution of urban carbon emissions

With the aim to further examine the features of carbon output's spatial distribution in Chinese prefecture-level cities, carbon emissions data from 2012 to 2020 are divided into five levels and visualized using ArcGIS 10.7 software. The results are plotted in Figure 1. There is a decreasing number of high-carbon emissions in cities and an increasing number of low-carbon emission areas. This shift indicates that carbon emission reduction measures are gradually taking effect nationwide. In terms of temporal changes, carbon emissions remained relatively stable between 2012 and 2016. However, from 2016 to 2020, there is a more apparent trend of reduction in carbon emissions. This trend is mostly associated with the adjustment of relevant national policies and stricter environmental protection measures. In summary, the spatial distribution features of urban carbon output exhibit clear regional and temporal changes. The eastern coastal and economically developed central regions are the main sources of carbon emissions. In contrast, the western and northeastern regions exhibit relatively lower emissions.



Note: This map is based on the standard map provided by the Map Technology Review Center (2022) of the MNR (Review No. GS (2022) 1873). No revisions or alterations have been made to the original map.

Figure 1. Characteristics of the spatial distribution of carbon emissions in Chinese cities in 2012, 2016 and 2020

5. Empirical results and analysis

5.1. Benchmark regression

Table 2 presents the results of the benchmark regression. Without controlling for other influencing variables, the results in column (1) show that the digital economy significantly reduces total urban carbon emissions. When Scope 1 carbon emissions (direct emissions) are used as the explanatory variable, column (3) shows a regression coefficient of –0.021, significant at the 1% level. This signifies that the digital economy has a significantly negative impact on direct carbon emissions.

By controlling for other variables affecting carbon emission levels, the regression model is re-validated for the four explanatory variables. Combining the results of column (2) and (4), when control variables are added, the regression coefficients of the interaction terms improve and remain significant at the 5% and 1% levels, respectively. This confirms the initial hypothesis 1.

Table 2. Benchmark regression results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables	Inco	Inco	Inco1	Inco1	Inco2	Inco2	Inco3	Inco3
bigdata	–0.016**	–0.018**	–0.021***	–0.022***	–0.001	0.007	–0.008	–0.020
	(0.007)	(0.007)	(0.007)	(0.008)	(0.017)	(0.018)	(0.018)	(0.019)
Control	×	√	×	√	×	√	×	√
Year fixed effect	√	√	√	√	√	√	√	√
Id fixed effect	√	√	√	√	√	√	√	√
N	3,135	3,135	3,135	3,135	3,135	3,135	3,135	3,135
R^2	0.978	0.978	0.972	0.972	0.873	0.874	0.851	0.851

Note: * , **, and***mean significance levels at 10%, 5%, and 1%, respectively. Figures in parentheses represent robust standard errors.

5.2. Robustness tests

5.2.1. Parallel trends test

This study, drawing on methodologies of Louis (1993) (Jacobson et al., 1992) and Beck et al. (2010), observes the timing of adopting the Big Data Pilot Zone policy and examines the policy effect using event analysis, expressed in the model:

$$\ln co_{it} = \partial + \sum_{-3}^{3} \theta_t bigdata_i \times post_t + + \varphi Control_{it} + \sigma_i + \tau_t + \varepsilon_{it}. \quad (7)$$

The variable definitions in this equation are consistent with those in Equation (1). The coefficient θ_t, representing the variation in carbon emissions between pilot and non-pilot cities in the t years following the establishment of the pilot zone, is the focus of this study. Figure 2 shows that before the pilot zone policy was adopted, the coefficient estimates for the experimental and control groups did not differ significantly from 0. This indicates no significant change in urban carbon emissions occurred before the pilot zone approval, suggesting that the selected samples satisfy the parallel trend assumption prior to policy implementation.

Since the adoption of the pilot zone policy, the initial year of implementation showed immediate results due to the policy's robustness. However, the first year's impact was limited as the policy required an adaptation period. During this time, enterprises and local governments needed to adjust to the new requirements and changes.

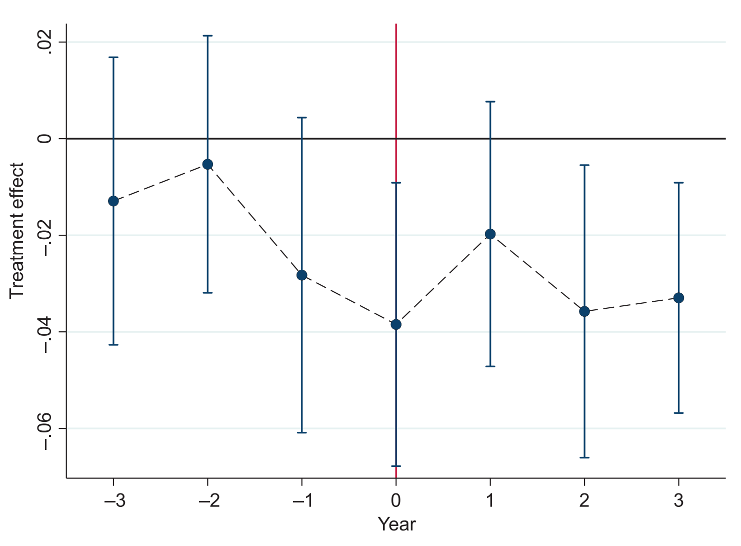


Figure 2. Parallel trends test

5.2.2. PSM-DID estimation

The balance test determines the validity of the PSM, which ensures no substantial difference exists between the sample-matching characteristic variables of the control and treatment groups. Figure 3 illustrates that most variables' standardized bias diminishes following matching, indicating that the propensity score matching system successfully eliminates potential endogeneity and selection bias issues. This, in turn, affirms the conclusions' robustness of this study.

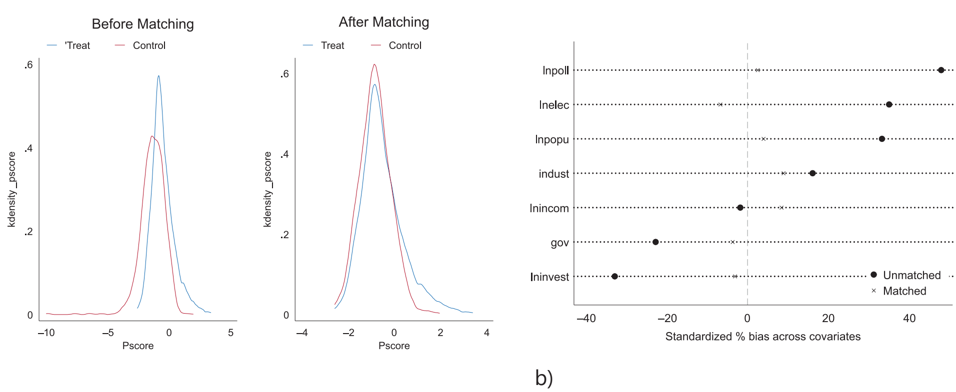


Figure 3. Balancing Trend Test: a – representing Kernel density distribution; b – representing Standardized deviation diagram of each variable

5.2.3. Policy inference testing

During the sample period (2011–2021), other policies related to big data development and urban carbon emissions might also influence the results. For example, "Broadband China" demonstration cities, smart city construction, clean energy demonstration provinces and new energy demonstration cities. To address potential estimation bias introduced by these concurrent policies, this study includes in the benchmark regression model dummy variables for "Broadband China" demonstration cities (denoted as broadband), smart city construction (denoted as smart), clean energy demonstration provinces (denoted as clear) and new energy demonstration cities (denoted as new) to re-estimate Equation (1).

This revised estimation's results are displayed in Table 3, after simultaneously controlling for the four policies, the outcomes remain consistent with the baseline regression. Therefore, the core empirical findings are not affected by other relevant policies, confirming the robustness of the positive effect of the digital economy on urban carbon reduction.

Table 3. Robustness test for excluding policy effects

	(1)	(2)	(3)	(4)	(5)
Variables	lnco	lnco	lnco	lnco	lnco
bigdata	–0.018**	–0.018**	–0.018**	–0.018***	–0.017**
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
smart	0.002				0.002
	(0.008)				(0.008)
broadband		0.001			0.001
		(0.006)			(0.006)
clear			0.005		0.005
			(0.010)		(0.010)
new				-0.001	–0.001
				(0.008)	(0.008)
Control	√	√	√	√	√
Year fixed effected	√	√	√	√	√
Id fixed effected	√	√	√	√	√
N	3,124	3,124	3,135	3,135	3,124
R^2	0.978	0.978	0.978	0.978	0.978

Note: * , **, and*** mean significance levels at 10%, 5%, and 1%, respectively. Figures in parentheses represent robust standard errors.

5.3. Further analysis

5.3.1. Analysis of spatial Durbin model

When analyzing the impact of the digital economy on urban carbon reduction, it is important to recognize that cities are interconnected through economic, environmental, and other factors. This article is based on the adjacency weight matrix, and then applies the SDM model with spatial fixed effects and bidirectional fixed effects for regression analysis, aiming to further explore the spatial spillover effects of the digital economy on urban carbon emissions.

As shown in Table 4, the coefficients of bigdata are negative in models (1), (2), (5), and (6). Model (1) is significant at the 5% level, while models (2), (5), and (6) are significant at the

1% level. These results indicate that the development of the digital economy significantly reduces total and direct carbon emissions in local cities. The results for indirect and other carbon emissions are consistent with the baseline regression, showing a negative but insignificant effect. This suggests that the digital economy does not significantly impact these types of emissions. The specific spatial spillover effects are further analyzed through spatial effect decomposition, as detailed in Table 5.

Table 4. Benchmark regression results for the SDM

VARIABLES	BOTH				IND			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Lnco	Lnco1	Lnco2	Lnco3	Lnco	Lnco1	Lnco2	Lnco3
bigdata	–0.0355**	–0.0454***	–0.00959	–0.0186	–0.0401***	–0.0497***	–0.0145	–0.0242
	(–3.02)	(–3.39)	(–0.31)	(–0.55)	(–3.36)	(–3.67)	(–0.47)	(–0.72)
W&big-data	0.0255	0.0314	0.0288	–0.00622	0.0360*	0.0409*	0.0444	0.00562
	(1.68)	(1.82)	(0.72)	(–0.14)	(2.37)	(2.38)	(1.12)	(0.13)
rho	0.0447	0.0216	0.0337	0.00643	0.0956***	0.0639*	0.0462	0.0186
	(1.71)	(0.82)	(1.26)	(0.24)	(3.79)	(2.49)	(1.74)	(0.70)
sigma2_e	0.00573***	0.00740***	0.0397***	0.0462***	0.00591***	0.00759***	0.0400***	0.0466***
	(39.58)	(39.61)	(39.60)	(39.57)	(39.56)	(39.58)	(39.58)	(39.59)
r2	0.000375	0.0210	0.0173	4.21e-05	0.0989	0.0798	0.0438	0.128
N	3135	3135	3135	3135	3135	3135	3135	3135
Control	√	√	√	√	√	√	√	√
yearfix	√	√	√	√	×	×	×	×
idfix	√	√	√	√	√	√	√	√

Note: *, ** and *** mean significance levels at 10%, 5%, and 1%, respectively. Figures in parentheses represent T value.

5.3.2. Decomposition effect analysis

As shown in Table 5, the coefficient for the direct effect of big data is negative. This indicates that the development of the digital economy significantly reduces both total and direct urban carbon emissions, even after accounting for spatial effects, the digital economy continues to exert a significant influence on carbon emissions. As for the indirect effects, the coefficient in models (5) and (6) is positive and statistically significant, indicating a notable spatial spillover effect of the digital economy in these models.

Table 5. Spatial Durbin model decomposition effects regression results

VARIABLES	BOTH				IND			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Lnco	Lnco1	Lnco2	Lnco3	Lnco	Lnco1	Lnco2	Lnco3
bigdata	–0.0355**	–0.0454***	–0.00959	–0.0186	–0.0401***	–0.0497***	-0.0145	–0.0242
	(–3.02)	(–3.39)	(–0.31)	(–0.55)	(–3.36)	(–3.67)	(-0.47)	(–0.72)
W&big-data	0.0255	0.0314	0.0288	–0.00622	0.0360*	0.0409*	0.0444	0.00562
	(1.68)	(1.82)	(0.72)	(–0.14)	(2.37)	(2.38)	(1.12)	(0.13)

End of Table 5

VARIABLES	BOTH				IND			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Lnco	Lnco1	Lnco2	Lnco3	Lnco	Lnco1	Lnco2	Lnco3
Direct	–0.0353**	–0.0452***	–0.00922	–0.0184	–0.0394***	-0.0491***	–0.0139	–0.0240
	(–3.01)	(–3.38)	(–0.30)	(–0.55)	(–3.36)	(–3.67)	(–0.45)	(–0.72)
Indirect	0.0237	0.0296	0.0271	–0.00812	0.0337*	0.0385*	0.0432	0.00363
	(1.50)	(1.67)	(0.65)	(–0.18)	(2.13)	(2.16)	(1.06)	(0.08)
Total	–0.0116	–0.0155	0.0179	–0.0265	–0.00564	–0.0106	0.0293	–0.0204
	(–1.30)	(–1.57)	(0.77)	(–1.09)	(–0.61)	(–1.05)	(1.28)	(–0.86)
rho	0.0447	0.0216	0.0337	0.00643	0.0956***	0.0639*	0.0462	0.0186
	(1.71)	(0.82)	(1.26)	(0.24)	(3.79)	(2.49)	(1.74)	(0.70)
sigma2 e	0.00573***	0.00740***	0.0397***	0.0462***	0.00591***	0.00759***	0.0400***	0.0466***
	(39.58)	(39.61)	(39.60)	(39.57)	(39.56)	(39.58)	(39.58)	(39.59)
r2	0.000375	0.0210	0.0173	4.21e-05	0.0989	0.0798	0.0438	0.128
N	3135	3135	3135	3135	3135	3135	3135	3135
Control	√	√	√	√	√	√	√	√
yearfix	√	√	√	√	×	×	×	×
idfix	√	√	√	√	√	√	√	√

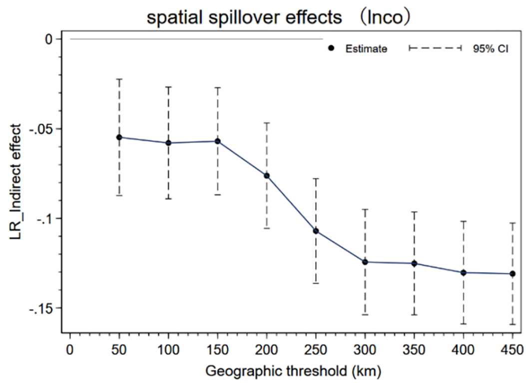
Note: * , **, and *** mean significance levels at 10%, 5%, and 1%, respectively. Figures in parentheses represent T value.

5.3.3. Spatial spillover effect

This article constructs the following spatial threshold distance matrix to further analyze the spatial spillover effects of the digital economy on urban carbon emissions levels.

$$w_{ij}^{d} = \begin{cases} \dfrac{1}{d_{ij}}, d_{ij} > d, d = 100, 200, 300, \ldots, 450 \\ 0, else \end{cases}. \tag{8}$$

In Equation (8), i and j respectively represent two cities, and d_{ij} represents the geographical distance between city i and city j. Based on Equations (5) and (8), estimate sequentially with a step size of 50 km, a draw Figure 4. The results show that within a geographical threshold of 450 km, the digital economy significantly reduces urban carbon emissions and shows a clear trend of fluctuating upward. When the geographic threshold reaches its peak between 300 km and 450 km, it has extremely high significance. Cities with geographic thresholds within the range of 300 km to 450 km exhibit stronger digital economy carbon emission spillover effects. This is primarily attributed to the higher similarity in economic development levels and environmental conditions among these cities. Such similarities facilitate smoother transmission of digital economy agglomeration effects and more synchronized industrial optimization and upgrading, thereby strengthening the effect of reducing carbon emissions.



Note: Due to the extremely similar spatial spillover effect maps of carbon emissions in the three ranges, in order to avoid further elaboration, only the spatial spillover effect map of total carbon emissions will be used as a demonstration for illustration.

Figure 4. Spatial distance spillover effect of digital economy

5.3.4. Regional heterogeneity

This article conducted heterogeneity grouping analysis on sample cities based on two dimensions, The results are shown in Table 6: geographical location and urban population size. From the perspective of geographical regions, the implementation of digital economy policies has significantly reduced urban carbon emissions in eastern China. Conversely, while the western and central regions' digital economies show potential positive effects on carbon emission reduction. This lack of significance is likely due to weaker development foundations, lower technological advancement, and insufficient policy support in these regions.

From the perspective of urban scale, reveals that digital economy policies greatly reduce emissions in cities with populations between 3 and 5 million. Conversely, small cities with populations under 3 million exhibit no significant carbon reduction effects. This lack of impact is attributed to a less developed digital economy and limited technology adoption. Large cities with populations exceeding 5 million, despite having active digital economies, face a diluted carbon reduction effect due to their complex urban structures and extensive economic systems. In these regions, the impact on emissions is less directly observable amid numerous influencing factors.

Table 6. Regional heterogeneity test

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	East	Middle	West	300	300–500	500
	Inco	Inco	Inco	Inco	Inco	Inco
bigdata	–0.017**	–0.014	–0.016	–0.016	–0.029***	–0.002
	(0.007)	(0.013)	(0.021)	(0.017)	(0.010)	(0.009)
N	1,320	880	935	1,111	880	1,144
R2	0.988	0.916	0.973	0.965	0.956	0.990
Control	√	√	√	√	√	√
Year fixed effect	√	√	√	√	√	√
Id fixed effect	√	√	√	√	√	√

Note: * , **, and *** mean significance levels at 10%, 5%, and 1%, respectively. Figures in parentheses represent robust standard errors.

6. Conclusions and policy recommendations

6.1. Conclusions

The main conclusions of this article are as follows:

(1) The advancing digital economy significantly reduces urban carbon emissions. This effect is especially pronounced in reducing direct urban carbon emissions. The robustness of this finding is confirmed through several tests, including the policy interference test, PSM-DID method, and parallel trend test.

(2) Heterogeneity studies indicate that the digital economy significantly reduces urban carbon emissions in the eastern region and medium-sized cities.

(3) The SDM analysis found that the development of the digital economy significantly reduces both total and direct carbon emissions in local cities. From the perspective of effect decomposition, after controlling for time and spatial effects, the direct impact of the digital economy on carbon emissions is the primary factor. The results of spatial spillover effects indicate that there is a positive spatial spillover effect in carbon reduction between cities.

6.2. Policy recommendations

Based on the study's findings, the following policy recommendations are suggested:

First, given the significant direct impact of the digital economy on carbon reduction, efforts should be made to encourage digital transformation in high-emission industries, leveraging digital technologies to improve energy efficiency and green innovation.

Secondly, the government should implement region-specific policies due to regional heterogeneity.

1. Eastern Region: Continue to bolster digital economy development to strengthen and expand its existing advantages in emission reduction.
2. Central and Western Regions: Enhance the technical support and infrastructure construction so as to boost the growth of digital economy and realize its potential for emission reduction.
3. Medium-Sized Cities: Provide targeted policy support, financial incentives, and technical assistance to enhance the digital transformation of medium-sized cities, thereby pursuing a more efficient reduction of carbon release.
4. Small Cities: Address the weak foundation of the digital economy in smaller cities by implementing targeted support measures to increase technology adoption and gradually achieve carbon emission reduction goals.
5. Large Cities: Develop comprehensive solutions for large cities by optimizing urban planning and management to improve resource utilization, promoting advanced digital technologies to pursue a more efficient utilization of energies, diminishing the intensity of carbon emission.

Thirdly, given the spatial spillover effects observed, the government should utilize the demonstration and leading roles of pilot regions. Strategically deploy pilot cities, encourage regional synergistic development, and enhance inter-regional cooperation and coordination.

6.3. Research prospects

Despite the considerable effort invested in this study, limitations persist, providing opportunities for further research. Future research directions can be improved from the following aspects: (1) Expanding the scope of research on spatial spillover effects and developing a multi-factor spatial weight matrix; (2) Conducting long-term tracking studies to examine the dynamic evolution of carbon reduction effects in the digital economy; (3) Exploring optimal pathways for the integration of the digital economy and traditional industries, providing a basis for differentiated carbon reduction policies.

The research results of this article indicate that formulating differentiated digital economy development strategies and strengthening inter-regional coordination are effective approaches to achieving carbon emission reduction goals. These findings not only enrich the literature on the digital economy and environmental governance but also offer valuable insights for policy formulation.

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