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Spatiotemporal Heterogeneities in the Impact of Chinese Digital Economy Development on Carbon Emissions

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Abstract: The digital economy plays an important role in reducing the global warming process. This paper explores the spatiotemporal heterogeneity impacts of the digital economy on provincial carbon emissions and its underlying mechanisms. Initially, this paper examines the inhibitory impact of the digital economy on carbon emissions, alongside the mediating role of economic agglomeration, at a theoretical level. Subsequently, it empirically explores the quantitative associations among the digital economy, economic agglomeration, and carbon emissions by utilizing Chinese provincial panel data spanning from 2000 to 2021. This investigation employed static and dynamic spatial Durbin models as well as mediation models to analyze the interrelationships. The results firstly revealed that the digital economy notably diminishes carbon emissions, with economic agglomeration playing a significant mediating role. This conclusion remained consistent even after substituting the explanatory variables and weight matrix, modifying the sample period, and conducting other robustness tests. Secondly, the impact of the digital economy on carbon emissions exhibited spatial spillovers. Compared with the impact on the local area, the impact on neighboring provinces was found to be weaker. Thirdly, carbon emissions showed a significant "snowball" effect in the time dimension. This paper emphasizes the important role of digital technology in curbing carbon emissions, and it provides some policy insights for studying the digital economy, economic agglomeration, and carbon emissions. Furthermore, it offers valuable insight and suggestions to reduce carbon emissions and realize the goal of the "dual-carbon" strategy.

Keywords: digital economy; carbon emission; economic agglomeration; spatial Durbin model; spillover effect

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1. Introduction

The escalating emissions of greenhouse gases, exemplified by carbon dioxide (CO_2), and consequent climate change phenomena, such as global warming, are presenting progressively severe challenges to the economic development, production, and livelihoods of human societies. Consequently, the imperative to reduce carbon emissions and achieve sustainable development has garnered consensus among nations worldwide [1]. Countries around the world are striving to achieve carbon peak and carbon neutrality. According to the United Nations Framework Convention on Climate Change, more than 130 countries and regions have proposed "zero carbon" or "carbon neutral" climate targets [2]. As the largest rising economies in the world, the BRICS countries accounted for about 43.19% of global CO_2 emissions in 2019 [3]. As one of the world's major carbon-emitting countries, China is under imminent pressure from energy conservation and emission reduction targets [4]. As a responsible, developing country, China pledged at the United Nations General Assembly to achieve the carbon reduction targets of "peak carbon and carbon neutrality" before 2030 and 2060, respectively. This poses a huge challenge for China, which is in a period of economic transition, to balance environmental pollution with economic growth. But at the same time, it also provides new opportunities for the Chinese economy to move towards high-quality green development and realize sustainable economic development [5].

Simultaneously, the digital economy, characterized as a novel economic paradigm, leverages data resources as production factors and depends on digital technologies such as big data, blockchain, and cloud computing to furnish advanced technological support and contribute factors toward realizing the objective of "dual carbon" [6,7], for example, the use of remote sensing technology to estimate carbon emissions and the use of blockchain technology to track a company's carbon footprint [8,9]. Currently, China's digital economy is in a period of rapid development. According to the Research Report on the Development of China's Digital Economy (2023) published by the China Academy of Information and Communications Technology (CAICT), the scale of the Chinese digital economy was projected to reach 50.2 trillion yuan in 2022, representing 41.5 percent of the country's GDP, a proportion equivalent to that of the secondary industry in GDP. Developing the digital economy not only reduces the cost of traditional industries and improves management and production efficiency but also favors the promotion of investment in renewable energy and the development of green infrastructure services, accelerating green information dissemination, etc. [10–14]. Hence, the advancement of the digital economy presents fresh opportunities for carbon mitigation and stands as one of the pivotal initiatives toward achieving the objective of carbon neutrality.

As important means and goals in the process of China's economic transformation and development, the development process and implementation effectiveness of the digital economy, energy conservation, and emission reductions are keys to determining whether China's green transformation can be successfully realized in the future [15]. The intricate relationship between the development process and implementation effectiveness has complicated and diverse influencing mechanisms. The development of the digital economy can not only directly provide technical support for China to achieve its emission reduction targets but also enhance the degree of economic agglomeration by strengthening the efficiency of resource allocation and reducing the loss of marginal costs, which in turn can reduce the level of carbon emissions. Hence, this paper integrates the concepts of the "digital economy", "economic agglomeration", and "carbon emissions" within a unified analytical framework. It explores the relationship between the digital economy and carbon emissions from both spatial and temporal perspectives, offering significant reference value for China's digital economy development in pursuit of the dual-carbon objective.

The three main contributions of this paper are as follows. Firstly, the paper engages in theoretical discussions concerning the pathways through which the rapid evolution of the digital economy influences carbon emissions. These pathways encompass the direct impact of the digital economy on carbon emission intensity, indirect influences through the augmentation of economic agglomeration, and the "snowball effect" of carbon emissions. Secondly, from a spatial perspective, empirical analyses are conducted to examine the spatial spillover effect of digital economy development on carbon emissions, employing the static spatial Durbin model while also verifying the mediating effect of economic agglomeration. Lastly, from a temporal standpoint, the paper investigates the path-dependent characteristics of carbon emissions by utilizing the dynamic spatial Durbin model based on Han–Phillips GMM.

The subsequent sections of the paper are organized as follows. Section 2 lays out the theoretical analyses and research hypotheses. Section 3 presents an empirical modeling study based on the research data and methodology. Section 4 presents results of robustness tests in terms of replacing the explanatory variables, the weight matrix, and the sample interval. Section 5 divides the sample into an eastern region and a central and western region for heterogeneity testing. Finally, we present conclusions and policy recommendations.

2. Theoretical Analysis and Hypotheses

2.1. The Impact of the Digital Economy on Carbon Emissions

In the global climate governance framework, reducing carbon emissions has become the core task of each country. The digital economy, as a novel paradigm propelling the evolution of the "technology–economy" interface, facilitates ecological and environmental governance, aligning with contemporary trends and imperatives for sustainable development. With the ongoing advancement of China's digital economy, the influence of the digital economy on carbon emissions can be examined from two perspectives. On the one hand, from a direct perspective, the development of the digital economy has given rise to a large number of digital industries, whose green levels are significantly higher than those of traditional industries and which are inherently environmentally friendly [7,16]. Secondly, digital technologies are gradually penetrating traditional industries and accelerating the process of industrial digitization; Wang et al. showed that the development of digital economy models such as digital finance and online trade has contributed to the high-quality development of China's energy resources and slowed down the growth of carbon emissions [15]. Industrial digitization not only enhances the energy efficiency of traditional industries, hastens the production transformation of conventional sectors, and fosters shifts towards industrial intelligence and sustainability but also facilitates improvements in energy conservation and emission reduction efficiency, diminishes electricity consumption intensity, and enables the sharing of energy and carbon emissions, thereby propelling the green sharing economy [17–21]. This is conducive to a more efficient and environmentally friendly production process, thereby reducing the level of carbon emissions and ultimately achieving green economic development. Thirdly, as the digital economy evolves, there is a concurrent rise in the extent of the tracking and management of carbon emissions within the production process. For example, Fasogbon and Igboabuchukwu showed that real-time carbon footprinting techniques based on energy consumption offer a broad potential applications for quantifying and managing carbon emissions [22]. Fourthly, the increased level of development of the digital economy can not only reduce industrial carbon emissions from business production but also reduce consumers' living carbon emissions. For example, the rapid development of the digital economy has given rise to new forms of online trade, video conferencing, cloud-based information sharing, etc., which greatly reduce the frequency of offline travelling and trade, thus reducing the carbon emissions generated by offline economic activities [23]. Moreover, green consumption platforms, green consumption products, etc., which are built on digital technologies, have greatly enhanced people's environmental awareness while facilitating their lives [24].

On the other hand, from an indirect perspective, the digital economy can affect the level of carbon emissions by changing the concentration of production and life within a region. The concentration of economic activities within a region is commonly measured by economic agglomeration indicators [25]. The digital economy can integrate and share fragmented data and knowledge to form a systematic and scaled data and information network, break the original information barriers between different regions and industries, and reduce the cost of searching for information, thus increasing economic agglomeration. Further economic agglomeration can affect the level of carbon emissions by exerting positive externalities such as factor allocation advantages and strengthening knowledge and technology spillovers [26]. Specifically, the "network agglomeration effect" of the digital economy is beneficial to all kinds of economic entities attempting to break the original form of agglomeration constrained by geographic space; these entities can use digital technology to transform this constrained agglomeration into a digital network agglomeration mode centered on data and information, thus increasing the degree of economic agglomeration, which in turn has an impact on the level of carbon emissions. It has been shown that an increase in economic agglomeration will have a two-way impact on the level of carbon emissions. The scale effect of economic agglomeration results in an augmentation in the spatial concentration of economic activities and a gradual expansion in output scale, consequently resulting in an increase in carbon emissions per unit of space and thereby engendering adverse environmental externalities [27,28]. The economies of scale generated by economic agglomeration can enhance production efficiency and mitigate energy consumption and transportation costs through technology spillovers and knowledge sharing, thereby creating positive environmental externalities [11,29,30]. Shao et al. noted that the ascent of Chinese urban agglomerations and the escalating level of economic agglomeration have favorably propelled China's energy-saving and emission reduction endeavors, facilitating the adjustment process of energy-saving and emission reduction technological innovation [31]. Therefore, based on the above analysis, we propose H1.

H1. *The digital economy not only directly reduces carbon emissions but also indirectly reduces carbon emissions by increasing economic agglomeration.*

2.2. Spatial Spillover Effects of the Digital Economy on Carbon Emissions

The development of digital technology and carbon emission levels in China is uneven. From a regional perspective, the level of digital technology development is higher in the east, while the west lags behind. The level of carbon emissions as a whole is characterized by a high level in the east and a low level in the west. As a new driving force for economic development, the digital economy breaks the traditional constraints of geography, information sharing, and resource flow, and it promotes unconscious "exchanges" between regions by strengthening the free flow of production factors such as information, technology and digital resources in space, which is conducive to the integration of industries, carbon emission reductions, technology sharing, and so on between different regions. First of all, digital technology is creative and pervasive, and it will have a spillover effect on the development of neighboring regions. Xue et al. showed that the development of a digital economy will increase the complexity of the supply chain and promote the development of the information and communication technology (ICT) industry [32]. This not only helps to reduce local carbon emissions but also generates spatial spillovers to nearby areas. Second, the development of digital technology accelerates the speed of information dissemination, which amplifies spatial demonstration and competition effects [33,34]. On the one hand, the digital economy weakens the law of diminishing technological spillovers due to geographical distance and strengthens the demonstration effect of spatial spillovers. This helps to guide different regions to learn from each other about carbon reduction and emission reduction technologies. The rapid development of the digital economy has given rise to a large number of carbon-reducing technologies, which not only help to reduce their own carbon emissions but also influence the carbon emission reductions of neighboring provinces in the process of their wide dissemination. As a result of the demonstration effect, neighboring provinces will follow the example of the provinces with the faster development of carbon emission reductions and adjust their production and consumption patterns, and the advanced regions will have a subtle demonstration effect on the lagging regions [35]. On the other hand, propelled by the "dual-carbon" goal, carbon reduction and emission mitigation have emerged as shared objectives among all provinces, leading to inter-provincial competition. Due to the competition effect, in order to better achieve the goal of carbon emission reduction, provinces will actively compete with each other in terms of talent, technology, environmental regulations, etc. Zheng et al. pointed out that the competition effect is asymmetric among provinces with different degrees of economic agglomeration [36]. Provinces with a low degree of economic agglomeration are more likely to receive the competition effect, which will exacerbate the spatial spillover effect of the digital economy on carbon emissions through indirect channels. Therefore, based on the above analysis, we propose H2.

H2. *The digital economy can affect carbon emissions in neighboring regions through spatial spillovers.*

2.3. The Snowball Effect of Carbon Emissions

Building upon the examination of the spatial spillover effect of the digital economy on carbon emissions, this paper additionally explores the temporal trajectory dependence of carbon emissions. Temporal path dependence refers to the fact that carbon emission levels are affected by not only the development level of the digital economy in the current period but also the carbon emission levels in the previous period, i.e., there is a "snowball" effect on carbon emission levels [37]. Provinces with higher carbon emission levels tend to have a closer relationship with high energy-consuming industries and traditional energy sources in their production methods, industrial structure, and energy consumption. In the process of low-carbon transition, they face greater difficulties in carbon emission reduction. For example, as the energy rebound effect is significantly higher for energy-intensive industries than for other provinces, it will reduce the carbon emission performance of energy-intensive industries [38]. Coal-producing provinces such as Shanxi and Inner Mongolia have more energy-intensive industries. Compared with other provinces, provinces with a higher traditional energy dependence have worse carbon emission performance due to the energy rebound effect, and the time accumulation effect of carbon emission levels is more obvious. Scholarly research shows that cities that implement low-carbon construction earlier can have stronger carbon emission reduction capacities by reserving professionals and adjusting policy tools [39,40]. Therefore, based on the above analyses, this paper proposes H3.

H3. *Carbon emission levels are affected by both the spatial spillover effects of the digital economy and the snowball effect of carbon emission levels.*

3. Methods

3.1. Model Settings

To investigate how the digital economy directly influence carbon emissions, we first constructed a benchmark model for the direct impact mechanism, as shown below:

$$ce_{i,t} = \alpha_0 + \alpha_1 dig_{i,t} + \alpha_2 sdig_{i,t} + \alpha_c Z_{i,t} + \mu_i + \delta_t + \varepsilon_{i,t} \tag{1}$$

where $ce_{i,t}$ represents the carbon emission of the province i during the period t, $dig_{i,t}$ represents the digital economy level of the province i during the period t, and $Z_{i,t}$ stands for the control variables. μ_i and δ_t represent individual and time fixed effects, respectively. $\varepsilon_{i,t}$ represents random disturbance.

Secondly, in addition to the direct impact effect embodied by Model (1), there may be an indirect mechanism of action between the digital economy and carbon emissions. Based on previous analyses, this paper tested whether economic agglomeration (ag) is a mediating variable between the two via the stepwise regression method [41]. The first step involves estimating Model (1) and examining the overall impact of the digital economy on carbon emissions. If α_1 is statistically significanicates support for the total effect of the digital economy. In the second step, we constructed the benchmark regression equations for dig versus ag and dig and ag versus ce. To assess the presence of a mediating effect, we examined the significance of β_i, γ_1, and γ_2. The specific settings of the stepwise regression model are as follows:

$$ag_{i,t} = \beta_0 + \beta_1 dig_{i,t} + \beta_c Z_{i,t} + \mu_i + \delta_t + \varepsilon_{i,t} \tag{2}$$

$$ce_{i,t} = \gamma_0 + \gamma_1 dig_{i,t} + \gamma_2 ag_{i,t} + \gamma_3 sag_{i,t} + \gamma_c Z_{i,t} + \mu_i + \delta_t + \varepsilon_{i,t} \tag{3}$$

where $ag_{i,t}$ represents the economic agglomeration of the province i during period t and $sag_{i,t}$ is the square term of $ag_{i,t}$. If β_1 and γ_2 are significant, the indirect effect exists. Then, the third step is to test whether the coefficient γ_1 is significant. If γ_1 is not significant, the direct effect does not exist, indicating that there is only a mediating effect known as the full mediating effect. If γ_1 is significant, the direct effect is also significant and is called the partial mediation effect.

Thirdly, to delve deeper into the influence of the digital economy on carbon emissions, we analyzed the spatial spillover effects within the mediation model framework. Additionally, we examined the spatial spillover effect of the digital economy on carbon emissions by incorporating their spatial interaction term into Model (1), which was further expanded into a spatial panel econometric model:

$$ce_{i,t} = \alpha_0 + \rho_1 Wce_{i,t} + \phi_1 Wdig_{i,t} + \phi_2 Wag_{i,t} + \phi_c WZ_{i,t} + \alpha_1 dig_{i,t} + \alpha_2 ag_{i,t} + \alpha_3 sag_{i,t} + \alpha_c Z_{i,t} + \mu_i + \delta_t + \varepsilon_{i,t} \tag{4}$$

where ρ represents the spatial lag coefficient and W represents the spatial weight matrix, which indicates the relationship of each province. Model (4) incorporates the combined impact of the digital economy and carbon emissions on carbon emissions with spatial lagged effects, termed the spatial Durbin model (SDM).

Finally, we comprehensively considered the dynamic spillover impacts of the digital economy and carbon emissions. These encompassed potential path-dependence characteristics of carbon emissions in the temporal dimension, as well as the endogeneity issue arising from the potential bidirectional causality between carbon emissions and economic and technological factors [42]. Therefore, we introduced a lag period of ce and set up the following dynamic spatial panel model:

$$ce_{i,t} = \eta_0 + \theta_1 Wce_{i,t-1} + \theta_2 Wdig_{i,t} + \theta_3 Wag_{i,t} + \theta_c WZ_{i,t} + \eta_1 ce_{i,t-1} + \eta_2 dig_{i,t} + \eta_c Z_{i,t} + \mu_i + \delta_t + \varepsilon_{i,t} \quad (5)$$

where $\theta_1, \theta_2, \theta_3$ and θ_c represent the elasticity coefficients of the spatial interaction terms for the explanatory variables, the core explanatory variables, and the control variables, respectively. Model (5) can simultaneously test the impact of the digital economy on carbon emissions and examine the time lag effect of carbon emissions.

3.2. Spatial Weighting Matrix Settings

A spatial weighting matrix is used to reflect the effect that the neighborhood explanatory variables have on the explained variables. Traditional weight matrices include the 0–1 matrix and neighborhood matrix [17]. In recent years, as economic and trade exchanges have become closer, the spillover effect between regions has been affected by not only geographical factors but also economic conditions. Therefore, we employed the following spatial adjacency matrix by combining the economic development status of each province and geographical distance:

$$W = \begin{cases} \frac{x_i x_j}{d_{ij}^2}, i \neq j \\ 0, \ i = j \end{cases}$$

where x_i and x_j represent the GDP per capita for provinces i and j, respectively. d_{ij} represents the geographical distance between provinces i and j.

3.3. Variable Descriptions

3.3.1. Explained Variable

We focused on the variable of carbon emission (ce). We estimated carbon emissions of provinces based on the measuring method provided by the United Nations Intergovernmental Special Committee on Climate Change (IPCC) and the consumption of eight major fossil energy sources in China. The eight major fossil energy sources are raw coal (10,000 tons), coke (10,000 tons), crude oil (10,000 tons), gasoline (10,000 tons), paraffin (10,000 tons), diesel fuel (10,000 tons), fuel oil (10,000 tons), and natural gas (100 million m^3). The specific calculation formula is as follows.

$$ce_{i,t} = \frac{CE_{i,t}}{L_{i,t}} = \frac{\sum_{n=1}^{8} c_n E_{n,i,t}}{L_{i,t}}$$

where $c_n (n = 1, 2, \cdots, 8)$ represents the carbon emission factors for the eight main fossil energy sources, $E_{n,i,t}$ represents the consumption of the energy n in province i in period t, and $L_{i,t}$ represents the total population of province i in period t.

3.3.2. Core Explanatory Variable

The central explanatory variable examined in this paper is the digital economy (dig). We constructed an index system to measure the digital economy. The index system includes the length of long-distance fiber-optic cables; the number of people employed in the information transmission, software and information technology services industry; the turnover of the technology market; the total volume of telecommunications business; and the number of mobile phone subscribers. Then, to objectively measure the level of the digital economy, we applied the entropy method. The specific process of the entropy method is as follows.

Firstly, the indicators are dimensionless. When the indicator x_{ij} is positive,

$$b_{ij} = \frac{x_{ij} - m_j}{M_i - m_j}$$

where M_i and m_j are the maximum and minimum of x_{ij}, respectively. When the indicator is negative,

$$b_{ij} = \frac{M_j - x_{ij}}{M_i - m_j}$$

Secondly, the indicators are normalized:

$$P_{ij} = \frac{b_{ij}}{\sum_{j=1}^{n} b_{ij}}$$

Thirdly, the entropy value of the indicator is calculated.

$$I_j = -k\sum_{i=1}^{m} P_{ij}\ln\left(P_{ij}\right),\ j = 1,2,3,\cdots,m$$

where k is a constant and $k > 0$, usually taken as $k = 1/\ln(m)$. I_j is greater than zero.

Fourthly, the entropy weights of the indicators are determined.

$$w_j = \frac{1 - I_j}{\sum_{j=1}^{m}\left(1 - I_j\right)}$$

Finally, linear weighting was applied to obtain the final composite evaluation index.

$$y_i = \sum_{j=1}^{m} w_j \times P_{ij}$$

3.3.3. Mediator

Based on the theoretical analysis presented above, this study chose economic agglomeration (ag) as the mediator to test the mediating mechanism. Drawing on Zhang et al., we used the number of employed people per unit area to measure the degree of economic agglomeration in each province [43]. In addition, existing studies show that there is a non-linear relationship between economic agglomeration and carbon emissions [44]. Therefore, we added ag and its quadratic term (sag) to the regression model.

3.3.4. Control Variables

In order to more comprehensively analyze the spillover effects of the development of the digital economy in carbon emissions, it is also necessary to study the control variables that may have an impact on carbon emissions. Therefore, the following control variables were selected in this paper: economic development (py), for which GDP per capita was used to control for possible non-linear effects of the level of economic development; industrial structure, which is expressed as the share of value added of the secondary industry in GDP (ig) and the share of value added of the tertiary industry in GDP (sg), respectively; technological progress (rd), characterized by patents granted per 100 R&D personnel; non-farm output (lp), represented by consumption expenditure per urban resident; urbanization (rm), characterized by urban population density; and talent development (pt), characterized by the human capital index in the China Human Capital Report (2022).

3.4. Data Sources and Descriptive Statistics

This study employed China's provincial-level panel data from 2000 to 2021, selected to ensure the accuracy of research and availability of data. The data of Tibet, Hong Kong, Macao and Taiwan were excluded due to a severe lack of relevant data. Primary sources for this article included the China Statistical Yearbook, the China Energy Statistical Yearbook and provincial statistical yearbooks. Table 1 presents the results of the descriptive statistics.

Table 1. Statistical description of variables.

	Variable	N	Mean	Std	Min	Max
Dependent Variable	ce	660	2.9794	2.8883	0.2857	25.6360
Independent Variable	dig	660	0.0753	0.0809	0.0012	0.6186
Mediator Variable	ag	660	4.8006	1.3008	1.3474	7.6828
Control Variable	py	660	3.8482	3.0473	0.2662	18.398
	ig	660	0.4684	0.2994	0.0658	4.9961
	sg	660	0.4531	0.2776	0.1008	4.1660
	lp	660	9.4494	0.6145	8.1952	10.8453
	rd	660	2.9684	0.8564	0.2109	6.1585
	rm	660	7.5874	0.7407	3.2581	8.7495
	hc	660	6.8544	0.8100	4.9562	8.8030

Based on Table 1, the minimum value of ce is 0.2857, the maximum value is 25.6360, and the standard deviation is 2.8883, implying substantial variance in per capita carbon emissions among provinces throughout the sampling period. Similarly, the disparity between the minimum and maximum values of dig is 0.6174, indicating significant discrepancies in digital economy development across provinces as well.

4. Empirical Results

4.1. Benchmark Regression

Column (1) in Table 2 presents the findings from the estimation of the impact of the digital economy on carbon emissions within the benchmark regression model. Here, the estimated coefficient of the primary explanatory variable, dig, demonstrates a statistically significant negative effect. This indicates that the development of the digital economy reduces carbon emissions, which is in line with the findings of Zhang and Liu [45,46]. In addition, the coefficients of py and ce exhibit a significant positive correlation, whereas the coefficients of spy and ce demonstrate a significant negative correlation. This suggests an inverted U-shaped relationship between per capita income and carbon emissions. Furthermore, ig presents a positive and statistically significant coefficient, implying that the rising proportion of the secondary industry within the GDP correlates with increased carbon emissions. Conversely, sg displays a significantly negative coefficient, indicating that the increasing proportion of the tertiary industry within the GDP is associated with a reduction in carbon emissions. The coefficient of ig is positive and significant, suggesting that the growing share of the secondary industry in GDP will elevate carbon emissions. Conversely, the coefficient of sg is notably negative, implying that with a higher proportion of tertiary industry in GDP, carbon emissions decline. This phenomenon might be attributed to the dominance of manufacturing activities within the secondary industry, which results in substantial emissions of carbon-containing pollutants during the manufacturing process, consequently escalating carbon emissions [7]. The tertiary sector, predominantly composed of the financial and service industries, plays a dominant role. A rise in the tertiary sector's contribution to GDP facilitates the mitigation of carbon emissions during economic development. The significant positive coefficient of lp implies that higher per capita non-agricultural output increases carbon emissions, which may mainly be due to the fact that China is mainly driven by the development of the manufacturing sector. Thus, the rise in non-agricultural output primarily stems from the advancement of the secondary industry, resulting in a notable positive correlation between lp and ce. The coefficient of Rd is negative but not significant. This may be due to the low number of carbon-related patents granted in China. The coefficient of rm is significantly positive, indicating that regions with high population densities have higher levels of carbon emissions.

Table 2. Benchmark regression and mediating effect test results.

Variable	**ce** **(1)**	**ag** **(2)**	**ce** **(3)**
dig	−11.1086 *** (−4.7854)	−0.2105 ** (−2.3031)	−10.4128 *** (−4.6981)
ag	\	\	13.9921 *** (7.8503)
sag	\	\	−1.3154 *** (−6.6533)
py	0.6586 *** (3.5633)	0.0499 *** (6.9218)	0.4567 *** (2.6485)
spy	−0.0364 *** (−3.9602)	−0.0023 *** (−6.8703)	−0.0241 *** (−2.9316)
ig	2.4163 ** (2.2936)	0.0915 * (1.8306)	2.7003 ** (2.5162)
sg	−2.7732 ** (−2.5041)	−0.1578 *** (−2.7849)	−2.1980 ** (−1.9860)
lp	3.2146 ** (2.4673)	0.0098 (0.1933)	1.2671 (1.0448)
rd	0.0295 (0.1554)	−0.0375 *** (−4.7546)	0.3245 * (1.7120)
rm	0.4546 *** (3.2785)	0.0083 (0.9955)	0.2385 * (1.8079)
hc	−4.8212 * (−1.7176)	−1.7014 *** (−15.3865)	−7.6008 ** (−2.1707)
shc	0.2366 (1.3558)	0.0820 *** (12.6329)	0.4572 ** (2.2070)
Constant	−9.9639 (−0.5432)	14.8443 *** (24.2531)	−14.7793 (−0.6736)
IFE	YES	YES	YES
TFE	YES	YES	YES
R2	0.7815	0.9980	0.8037
F	55.34	8187.65	65.76

Note: The values in parentheses are t-values or z-values. In the table, ***, **, and * indicate that the regression results pass the significance test at the 1%, 5%, and 10% confidence levels, respectively. The same applies to subsequent tables.

4.2. Mediating Effect Regression

Based on the previous theoretical analyses, the digital economy not only has the ability to reduce carbon emissions but also affects economic agglomeration, thus changing carbon emissions. Therefore, in addition to directly affecting carbon emissions, the digital economy also indirectly affects carbon emissions through economic agglomeration [47]. In summary, we provide an in-depth study of the mediating effect of economic agglomeration. The results of this mediating mechanism are shown in columns (2) and (3) of Table 2.

Column (1) shows that the digital economy can significantly reduce the level of carbon emissions. Then, column (2) verifies that there is a significant negative correlation between the digital economy and economic agglomeration. In column (3), the mediating variable is added to the regression equation of the digital economy affecting carbon emissions. By observing the coefficient of dig, it can be seen that the regression coefficient of dig for ce in Model (3) is significant at the 1% level, and the value is increased compared with that of Model (1). This suggests that the increase in economic agglomeration is the mechanism of action of the digital economy to reduce the level of carbon emissions, and this result supports H1.

4.3. SDM

Firstly, before conducting spatial econometric analyses, it was necessary to test whether there are spatial effects of carbon emissions and the digital economy. In this paper, we used Moran's I index to calculate the spatial autocorrelation of the two under the nested matrix of economic geography, and the results are shown in Table 3.

Table 3. Moran's I test results.

	ce	**dig**
Moran's I	0.090 *** (7.477)	0.343 *** (27.997)

*** indicates that the regression results pass the significance test at the 1% confidence level.

The results in Table 3 show that the Moran's I index for both ce and dig are significant at the 1% level under the economic geography weight matrix. This indicates that there is a significant spatial autocorrelation between the digital economy and carbon emissions in the provinces within the sample interval. Therefore, dig and ce show a clustering phenomenon in their spatial distribution.

Moving on, referring to Elhorst [48], this paper sequentially conducted the Hausman test, the LM test and the LR test. The spatial Durbin model (SDM) with spatiotemporal double fixed effects was finally identified as the optimal choice. The results are shown in column (1) of Table 4.

The estimation results in Table 4 show that the elasticity coefficient of dig is −13.7636 and significant at the 1% level. This result indicates that the current development of the digital economy significantly reduces carbon emissions in the provinces. Meanwhile, both the regression coefficients of ag and sag are statistically significant at 11.9170 and −1.0768, respectively. This observation suggests that economic agglomeration exhibits an inverted U-shaped relationship with carbon emissions. Specifically, when economic agglomeration measures less than 5.5335, carbon emissions display a positive correlation with economic agglomeration, indicating that the scale effect of the economy outweighs the economy of the scale effect during this phase. Conversely, when economic agglomeration exceeds 5.5335, a negative correlation emerges between the two variables. At this time, the environmental dividend brought about by economic agglomeration gradually appears, and the scale economy effect is greater than the scale effect.

Further examining the spatial spillover effect of the digital economy among provinces shows that the regression coefficient of dig is negative and significant at the 1% level, which indicates that the development of the digital economy in neighboring provinces can significantly reduce their carbon emissions. However, the regression results of the interaction term between the digital economy and weight matrix do not directly reflect the marginal impact of the digital economy on carbon emissions. Therefore, we adopted the partial differentiation of variable changes for interpretation, i.e., using direct and indirect effects to study the heterogeneous impact of the digital economy on carbon emissions in local and other regions [49].

Table 4. Static and dynamic SDM results.

Variable	SDM			Dynamic SDM
	ce (1)	**ce (2)**	**ag (3)**	**ce (4)**
L.ce	\	\	\	1.4998 *** (24.97)
dig	−13.7636 *** (−7.7547)	−16.6513 *** (−9.2088)	−0.3427 *** (−4.1404)	−3.7661 *** (−3.30)
ag	11.9170 *** (7.2632)	\	\	7.4042 *** (5.45)
sag	−1.0768 *** (−5.5107)	\	\	−0.7460 *** (−5.18)
W × dig	−106.8135 *** (−5.8491)	−142.4802 *** (−7.7829)	−2.7125 *** (−3.2674)	0.0049 *** (3.46)
W × ag	41.8668 *** (3.0521)	\	\	−0.0107 (−1.51)
W × sag	−3.1848 ** (−2.0496)	\	\	0.0015 (1.50)
Control variable	YES	YES	YES	YES
Direct Effect	−10.8741 *** (−6.2307)	−13.4744 *** (−7.5124)	−0.3101 *** (−3.7839)	\
Indirect Effect	−55.5802 *** (−4.6435)	−85.0672 *** (−5.6736)	−2.1323 *** (−2.9417)	\
Total Effect	−66.4543 *** (−5.2880)	−98.5416 *** (−6.2727)	−2.4424 *** (−3.2136)	\
LogL	50.9759	50.9759	50.9759	\
R^2	0.2313	0.2588	0.1476	0.2799

***, ** indicate that the regression results pass the significance test at the 1%, 5% confidence levels, respectively.

In column (1) of Table 4, the results demonstrate significant reductions in carbon emission levels within local and other areas due to the influence of the digital economy, as indicated by the direct, indirect, and total effect measures. This finding supports H2. Specifically, the developmental progression of the digital economy, concurrent with the advancing maturity of digital technologies, contributes to reductions in local carbon emission levels through both production and consumption channels, and it can also give full play to the economies of scale of economic agglomeration by enhancing the degree of economic agglomeration, thus reducing carbon emissions. At the same time, this progression can also inhibit carbon emissions in neighboring regions through spillover and demonstration effects.

Furthermore, based on the perspective of spatial correlation, we once again applied the stepwise regression method to verify the mediating role of economic agglomeration on the development of the digital economy affecting carbon emissions. In column (3) of Table 4, the regression coefficient of dig on ag is shown to be significant. Column (2) verifies that the regression coefficient of dig on ce is equally significant. Given that the regression coefficients of dig and ag on ce in column (1) are both significant at the 1% level, it can be said that the digital economy can still affect carbon emissions through economic agglomeration under the influence of spatial spillovers. Once again, H1 is proven.

4.4. Dynamic SDM

Most previous studies have focused on the static perspective to study the factors affecting carbon emissions, while this paper argues that carbon emissions have time-dependent characteristics. Therefore, the dynamic hypothesis that carbon emissions have a snowball effect is proposed. In this paper, we used the dynamic SDM to test H3, and the time lag term was introduced into Model (5). In order to overcome the biased estimation of the least squares method (OLS), the endogeneity problem of the great likelihood estimation (MLE), and the weak instrumental variable problem of the differential GMM, we referred to the Han–Phillips generalized moment estimation to estimate the dynamic SDM. The results are shown in column (4) of Table 4.

In Table 4, the coefficient of the lagged term of carbon emission is significantly positive at the level of 1%. This verifies that carbon emissions have the dynamic snowball effect. Therefore, when the carbon emissions of the previous period are at a high level, the carbon emissions of the next period will continue to be high. Thus, H3 is proven. Specifically, every increase of one unit of carbon emission in the current period will lead to an increase of 1.4998 units of carbon emission in the next period. This means that along with the snowball phenomenon of carbon emissions, China's current carbon emission reduction work has a serious urgency and arduousness. Analyzing column (1) of Table 4 shows that the impact of the digital economy and economic agglomeration on carbon emissions changes after considering the path-dependent characteristics of carbon emissions. The impact of the digital economy and economic agglomeration on local carbon emission levels remains significant, but their spatial spillover impact on the neighboring regions decreases.

5. Robustness Test

The regressions discussed earlier provide evidence that the digital economy reduces carbon emissions and that economic agglomeration plays a mediating role. To further ensure the credibility of these results, this paper checked the robustness from several perspectives. The results are presented in Table 5.

Table 5. Robustness test results.

Variable	SDM			Dynamic SDM			IV Method
	Changing the Dependent Variable (1)	Changing the Weight Matrix (2)	Changing the Sample Period (3)	Changing the Dependent Variable (4)	Changing the Weight Matrix (5)	Changing the Sample Period (6)	(7)
L.ce	\	\	\	1.5034 *** (16.49)	1.5068 *** (25.38)	1.5183 *** (9.12)	\
dig	−1.2691 *** (−5.5391)	−14.0533 *** (−7.7277)	−10.8760 *** (−7.4797)	−0.4520 ** (−2.19)	−3.8163 *** (−3.35)	−2.575 *** (−2.69)	−12.9828 *** (−4.6132)
ag	2.2049 *** (10.4523)	12.2122 *** (7.4250)	13.6653 *** (11.6922)	1.2595 *** (5.12)	7.5027 *** (5.53)	5.9623 *** (6.26)	13.3144 *** (8.1316)
sag	−0.1818 *** (−7.1967)	−1.0755 *** (−5.5049)	−1.4939 *** (−10.6148)	−0.1109 *** (−4.25)	−0.7544 *** (−5.24)	−0.6329 *** (−6.16)	−1.2763 *** (−6.8022)
W × dig	−5.5826 ** (−2.3485)	−103.0876 *** (−5.5331)	−78.6314 *** (−5.3996)	0.0006 ** (2.16)	0.0050 *** (3.50)	0.0028 ** (2.31)	\
W × ag	−2.7602 (−1.5107)	39.3231 *** (2.7741)	20.1965 ** (2.0648)	0.00003 (0.02)	−0.0108 (−1.47)	−0.0119 ** (−2.35)	\
W × sag	0.1043 (0.5023)	−2.9065 * (−1.8424)	−5.6515 *** (−4.5997)	0.0001 (0.78)	0.0015 (1.50)	0.0016 ** (2.31)	\
ρ	−1.0550 *** (−5.2206)	−0.8873 *** (−4.1582)	−1.2116 *** (−5.3394)	\	\	\	\
Direct Effect	−1.1062 *** (−5.0863)	−11.2082 *** (−6.3790)	−8.1922 *** (−5.8521)	\	\	\	\
Indirect Effect	−2.2449 * (−1.8639)	−51.4347 *** (−4.4195)	−32.4968 *** (−4.2135)	\	\	\	\

Table 5. *Cont.*

Variable	SDM			Dynamic SDM			IV Method
	Changing the Dependent Variable	Changing the Weight Matrix	Changing the Sample Period	Changing the Dependent Variable	Changing the Weight Matrix	Changing the Sample Period	(7)
Total Effect	−3.3511 *** (−2.6960)	−62.6430 *** (−5.1158)	−40.6889 *** (−5.0372)	\	\	\	\
Control variable	YES	YES	YES	YES	YES	YES	YES
Fixed Effects	YES	YES	YES	YES	YES	YES	YES
R2	0.1234	0.2252	0.2189	0.7372	0.3033	0.3191	0.8128

***, **, and * indicate that the regression results pass the significance test at the 1%, 5%, and 10% confidence levels, respectively.

5.1. Change the Explanatory Variable

This paper previously used the per capita carbon emissions of each province as the explanatory variable. In the current analysis, the total carbon emissions of individual provinces served as the explanatory variable, with the regression outcomes presented in columns (1) and (4) of Table 5. The findings indicate a persistently significant negative regression coefficient for dig. This indicates that the development of the digital economy has a significant reduction effect on both total and per capita carbon emissions, which is consistent with the benchmark regression results.

5.2. Change the Geographic Weighting Matrix

In addition to the economic–geographic nested matrix, this paper applied a geographic distance matrix (W2) for robustness testing. The results of the static and dynamic SDM regressions are shown in columns (2) and (5) of Table 5, respectively. The static SDM regression results in column (2) show that the elasticity coefficients and spatial elasticity coefficients of dig to ce are significantly negative, which is consistent with the previous results. The study suggests that the advancement of the digital economy contributes to a reduction in carbon emissions. The results from the dynamic spatial Durbin model (SDM) regression in column (5) indicate that the digital economy and carbon emissions of dig and L.ce exhibit significant negative spatial spillover effects and positive time cumulative effects, respectively. These findings align with prior research outcomes.

5.3. Change the Sample Interval

The impact of the digital economy on carbon emissions was analyzed using data from 2000 to 2021. However, the outbreak of COVID−19 at the end of 2019 had great impacts on domestic and international living and production activities. Hence, this study modified the sampling interval to encompass the years 2000–2019 to facilitate a more comprehensive evaluation of the influence exerted by the digital economy and economic agglomeration on carbon emissions. The findings are depicted in columns (3) and (6) of Table 5. Notably, no substantial alterations were observed in the parameter estimations and their associated significance, thus affirming the robustness of the results.

5.4. Endogeneity Treatment

The regression results show that the development of the digital economy can significantly reduce carbon emissions. However, due to the need for green development, regions with higher levels of carbon emissions will accelerate the promotion of local digital economy construction levels, so there may be a bidirectional causal relationship between them. This may lead to endogeneity problems. Thus, we chose the instrumental variable method to verify it. The key to solving an endogeneity problem is to choose appropriate instrumental variables, which need to satisfy the two assumptions of correlation and exogeneity. In other words, the instrumental variables should exhibit correlation with the endogenous explanatory variables while remaining uncorrelated with the random disturbance terms. Therefore, the lagged one period of dig was chosen as the instrumental variable for the endogeneity test in this study. The regression results in column (7) in Table 5 show that the impact of the digital economy on reducing carbon emissions is still significant at the 1% level after accounting for endogeneity. In addition, the results of the test for the under-identification of instrumental variables show that the Kleibergen–Paap rk LM statistic is 35.017, which corresponds to a p-value of 0.0000, significantly rejecting H0. The results of the test for weak instrumental variables show that the Kleibergen–Paap rk Wald F statistic of 197.034 is greater than the Stock–Yogo critical value at the 10 percent level. This justifies the selection of the instrumental variables used in this paper.

6. Heterogeneity Analysis

Due to variations in resource allocation and developmental stages, both the advancement of the digital economy and carbon emissions exhibit pronounced heterogeneity in regional distribution. Consequently, the influence of the digital economy on carbon emissions is likely to manifest heterogeneously across regions, warranting an in-depth examination. We conducted a heterogeneity regression analysis for the eastern, central, and western regions. The eastern region includes Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Hainan, Liaoning, Jilin and Heilongjiang. The central and western region includes Shanxi, Anhui, Jiangxi, Henan, Hubei, Hunan, Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia and Xinjiang.

Before conducting empirical analyses of regional heterogeneity, this paper first provides descriptive statistics on the differences between different regions. The results in Table 6 show that for carbon emissions, digital economy development, and economic agglomeration, the eastern region has higher values than the central and western region. The differences in the mean values of the variables between the two types of regions were found to be 0.1838, 0.0451, and 1.2761, respectively.

Table 6. Statistical description of variables in different regions.

Variable	Region	N	Mean	Std	Min	Max
ce	Eastern Region	286	5.3763	1.0023	0.0094	7.1497
	Central and Western Region	374	5.1925	0.9694	−0.2053	7.6496
dig	Eastern Region	286	0.1008	0.1028	0.0015	0.6186
	Central and Western Region	374	0.0557	0.0512	0.0012	0.3019
ag	Eastern Region	286	5.5237	0.9597	3.4298	7.6828
	Central and Western Region	374	4.2476	1.2564	1.3474	5.8578

Table 7 shows the static and dynamic SDM regression results for the eastern region and the central and western region. The findings presented in columns (1) and (2) indicate that the impact of the digital economy on carbon emissions is notably greater in the central and western region compared with the eastern region. This may be due to the fact that the development of the digital economy in the central and western region started later and is at a lower level than that of the eastern region, and it is now in the “novice dividend period”. On the other hand, the level of digital economy development in the eastern region is already high. While the continued advancement of the digital economy in the eastern region is anticipated to lead to a reduction in carbon emissions, the associated marginal utility is notably lower compared with that observed in the central and western region. Moreover, the coefficient of economic agglomeration in the eastern region exhibits a significant negative value, in contrast to the significantly positive coefficients observed in the central and western region. These findings suggest a negative correlation between economic agglomeration and carbon emissions in the eastern region, while a positive correlation was observed in the central and western region. A possible reason for this result is that the eastern provinces of China have a higher level of economic agglomeration and a more reasonable economic structure than the central and western provinces, which makes the economies of scale brought about by economic agglomeration greater than the scale effect and more fully releases the green emission reduction dividend. On the other hand, the development of economic agglomeration in the central and western region started late and to a low degree, which makes it difficult to use the effect of economies of scale. Thus, it is difficult for economic agglomeration to effectively reduce carbon emissions.

Table 7. Heterogeneity test results.

Variable	SDM		Dynamic SDM	
	Eastern Region (1)	**Central and Western Region (2)**	**Eastern Region (3)**	**Central and Western Region (4)**
L.ce	\	\	1.3512 *** (15.48)	1.7597 *** (20.33)
dig	−0.6698 ** (−2.0675)	−19.7209 *** (−4.1556)	0.4356 (1.19)	−15.1738 *** (−5.50)
ag	−4.5967 *** (−7.3620)	−6.5964 *** (−2.5883)	0.7113 (0.48)	5.2898 *** (2.66)
sag	0.3735 *** (5.9945)	0.5610 * (1.8350)	−0.1476 (−1.18)	−0.2993 (−1.12)
W × dig	−2.6689 (−1.5383)	−14.1425 (−0.3391)	0.0005 (0.29)	0.0564 *** (5.21)
W × ag	−1.8186 (−0.5570)	−94.5845 *** (−3.9273)	0.0826 *** (3.61)	−0.0166 (−0.45)
W × sag	0.3704 (1.3101)	3.3912 (1.1788)	−0.0072 ** (−3.22)	0.0080 (1.49)
Control variable	YES	YES	YES	YES
Fixed Effects	YES	YES	YES	YES
R2	0.5862	0.1655	0.7629	0.7015

***, **, and * indicate that the regression results pass the significance test at the 1%, 5%, and 10% confidence levels, respectively.

The outcomes presented in columns (3) and (4) of Table 7 demonstrate that the coefficients associated with the lagged terms of carbon emissions are all notably positive. This indicates that both the eastern region and the central and western region have significant time-dependent carbon emissions. This means that both the eastern region and the central and western region of China are facing urgent pressure to reduce emissions in the future, highlighting the importance of developing the digital economy and accelerating the task of reducing carbon emissions.

7. Discussion

In examining previous studies concerning the relationship between the digital economy and carbon emissions, this paper corroborates their findings that the digital economy significantly reduces carbon emissions and demonstrates a spatial spillover effect on neighboring provinces' carbon emission levels [50]. What sets this paper apart from prior research is its expansion beyond the spatial impact analysis of the digital economy on carbon emissions [51]. This paper extends the research perspective to encompass the temporal dimension, analyzing factors influencing carbon emission levels across both spatial and temporal dimensions. Consequently, this paper confirms the existence of a snowball effect on carbon emissions and addresses a gap in this research field. Naturally, this paper exhibits certain limitations. We outline the limitations as follows.

1. This paper solely examines the impact of economic agglomeration as a mediating variable on the relationship between the digital economy and carbon emissions. Given that the digital economy can influence carbon emissions through many mediating variables, future research could delve deeper into analyzing different mediating transmission pathways of the digital economy on carbon emissions.

2. This paper employs the entropy weight method to gauge the level of the development of the digital economy. Consequently, the weight coefficients assigned to variables such as the length of long-distance fiber-optic cables, turnover of the technology market, and total volume of telecommunications business remain constant, indicating fixed weights for each variable. However, given the evolving nature of the context, dynamic weighting methods like the dynamic factor method offer a more nuanced reflection of variable weights across different time periods, rendering them more pertinent. Therefore, future research could explore the utilization of dynamic weighting methods to develop an approach that is both more objective and better aligned with changes in the digital economy's development.

3. This paper examines the influence of China's digital economy development on the level of carbon emissions from a provincial perspective, potentially obscuring variations in economic development within each province. Subsequently, further in-depth investigation into the interaction between these factors, taking into account the specific development levels of various prefecture-level cities within each province, could be conducted.

8. Conclusions and Policy Implications

8.1. Conclusions

The digital economy presents significant potential for reducing carbon emissions in China. This paper aimed to investigate the mechanisms through which the digital economy influences carbon emissions. Empirical analyses were conducted using fixed-effect models, intermediary effect models, an SDM, and a dynamic SDM by utilizing provincial panel data spanning from 2000 to 2021. The study sought to substantiate the impact of the digital economy on carbon emissions, elucidate the intermediary role of economic agglomeration, and assess the heterogeneity among different provinces. Ultimately, the following conclusions were derived: (1) The digital economy can effectively reduce carbon emissions. It can either directly reduce carbon emissions or indirectly affect carbon emissions through economic agglomeration, and the emission reduction effect is significant in the eastern, central and western regions. (2) The digital economy has significant spatial spillover effects. While developing the digital economy to reduce carbon emissions, different provinces can also influence the carbon emissions of neighboring provinces through the channels of spillover, demonstration, and competition effects. (3) Carbon emissions have a significant snowball effect, i.e., provinces with higher leveld of carbon emissions in the previous period will have significantly higher leveld of carbon emissions in the next period.

8.2. Policy Implications

In light of the foregoing discoveries, we propose the subsequent policy recommendations:

(1) There are spatial gradient differences in China's digital economy development and carbon emissions. When setting carbon reduction targets, the government should set "dual-carbon" targets suitable for the level of development of different provinces according to the level of development of their digital economy.

(2) In the process of developing the digital economy, the government should pay close attention to the levels of economic agglomeration of different provinces. In regions characterized by limited economic agglomeration, such as the central and western areas, governmental intervention can be strategically employed to enhance the structure and density of economic agglomeration. This can be achieved by expediting the spillover impact of digital technology, leveraging the demonstrative influence of economic agglomeration observed in the eastern region, and fostering competitive dynamics.

(3) The government should consider the huge pressure of carbon reduction and emission reduction brought by the snowball effect on large carbon-emitting provinces.

The aim of controlling the overall national carbon emissions can be realized through the development of the carbon market, the facilitation of carbon emission trading among different provinces, and the formulation of a carbon emission compensation policy. Ultimately, the challenge of climate risk arising from greenhouse gas emissions can be reasonably addressed.

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