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The Impact of Digitalization on Carbon Emissions in China: A Spatial Analytical Perspective

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Abstract

The process of digitalization plays a significant and beneficial role in China's endeavors to regulate carbon emissions and accomplish its targets of carbon peaking and carbon neutrality. Hence, it is crucial to ascertain the spatial distribution of carbon emissions in China and analyse the impact of digital mitigation strategies on emissions. This study analyses 30 provincial panels in China to investigate the correlation between digitalization and carbon emissions. The spatial impact of digitalization on carbon emissions is verified using a dynamic spatial Durbin model. This article describes the geographical agglomeration characteristics of carbon emissions in China and visualized these by spatial and temporal mapping using ArcGIS software. The short-term and long-term direct effects and spatial spillover effects of digitalization on carbon emissions are examined. The findings indicate that digitalization and carbon emissions exhibited high levels of concentration. The substitution effect of digitalization on carbon emissions outweighs the use effect. Digitalization has direct and spatial spillover effects on carbon emissions, resulting in a cyclic accumulation effect over the long term. There are heterogeneity consequences of digitalization for carbon emissions in various places. The eastern region’s digitalization has the most significant influence on carbon emissions, followed by the central region and then the western region. The study proposes regional cooperation, digital technology, and optimization of industrial structure to achieve environmental regulatory targets. Governments should develop measures for the assessment of carbon stocks. This research has significant ramifications for the government in formulating environmental regulations that fostering high-quality economic development.

Keywords: Digitalization, Carbon Emission, Dynamic Spatial Durbin Model, Environmental Regulations

Introduction

Over the past few years, there has been a global digital revolution, characterised by substantial advancements in information and communication technology (ICT) in numerous countries. This revolution has pushed human society into the digital age (Zhang et al., 2020). This digitalization has transformed virtually every aspect of society, both in business and private lives. It is not only conducive to technological innovation, but also becomes an important driving force for economic growth (Sassi and Goaied, 2013). China's ICT industry is also booming under the trend of globalization. The 53rd Statistical Report on China's Internet Development states that the number of internet users in China reached 1.092 billion in 2023, and the internet penetration rate was 77.5 percent. Nevertheless, while striving for rapid economic growth, the issue of declining environmental quality has become more noticeable. As an illustration, substantial energy consumption is necessary for economic expansion, resulting in large carbon emissions (Liu et al., 2021). Haze, which is a form of air pollution, is becoming more severe in China's industrial cities (Chen et al., 2020). The Chinese government has established the objective of achieving a maximum level of carbon peak by 2030 and attaining carbon neutrality by 2060, which requires establishing concrete and realistic goals for reducing carbon emissions.

The relationship between digitization and carbon emissions is intricate. On the one hand, digitalization expansion contributes to the acceleration of carbon emissions by increasing the creation, usage, and disposal of digital items. For example, the escalation of electronic waste and the intensification of energy use in manufacturing have detrimental impacts on carbon emissions Yu et al (2023), which mean digitalization usually increases CO2 emissions (Asongu, 2018; Martins et al., 2019). On the other hand, digitalization is considered a solution to alleviate carbon emissions, to address vital environmental degradation such as climate change and air pollution. For example, digitalization can help to mitigate carbon emissions through increasing awareness of environmental protection and utilization of carbon emission reduction technology (Ozili, 2023; Sasikumar et al., 2023). China's carbon emission growth and digital development are highly negatively correlated indicating that digital development restrains carbon emission (Shen et al., 2023). In addition, the relation between digitalization and carbon emissions also depends upon the rebound effects of digitalization. The theory of rebound effects means that the long-term benefits of digital technology can be counterbalanced. If digitalization developments lead to reduced prices, the demand for digitalization products and services will increase, thereby increasing carbon emissions (Yuan et al., 2023).

Several research have demonstrated that the process of digitization has a substantial influence on environmental contamination, and furthermore, its channels of action have been investigated. The first channel factor is the industrial structure (Li et al., 2019; Tian et al., 2019). Digitalization facilitates the efficient distribution of labour and capital, leading to a transfer of the industrial structure towards higher value-added activities and the adoption of environmentally friendly practices. Consequently, this results in a reduction in pollutant emissions. The second channel factor is technological progress (Shahbaz et al., 2020; Yi et al., 2020). In the capacity of facilitating the exchange and dissemination of technology, digitalization promotes inter-regional technology trade and technology spillover. This is beneficial for the development and spread of green production technologies, and has a good effect on reducing emissions. The third channel factor is financial development (Cui et al., 2023). Internet finance can quickly match the capital demanders and suppliers of green technology projects, improve financial intermediation and financial transaction efficiency, and promote the innovation of green environmental protection technology, thus helping to reduce pollution emissions. However, an empirical study by Asongu and Nwachukwu (2016) argues that ICT enhances the financial sector by facilitating more access to credit for

businesses and families, and by improving the allocation of investments to stimulate economic growth Tchamyou et al (2019), hence, leading to a rise in air pollution. Therefore, the effect of digitalization on environmental quality because of financial development is unpredictable.
To summarise, while numerous studies have conducted valuable research on the influence of digitalization on environmental quality, there are certain limitations in the current study. When examining the elements that influence carbon emissions, researchers have considered several socio-economic aspects, including industrial structure, financial development, energy use, and technological progress. Nevertheless, the existing literature lacks to adequately emphasise the significance of studying the geographical spillover effects of carbon emissions. Furthermore, while standard non-spatial regression approaches such as the threshold effect model, the Generalised Moment Estimation method, and multi-phase double difference method are commonly employed, there is a scarcity of studies that utilise spatial measures. Due to airflow, the spatial distribution of carbon emissions is fluid, so regional carbon emissions are bound to have spillover effects. On the other hand, digital infrastructure transmits information through communication cables and signal base stations, and is not restricted by geographical constraints. Therefore, digital development also has spatial spillover effects. Therefore, the application of spatial econometric models is highly practical so that leaders can formulate effective policies to reduce carbon emissions.
This paper aims to introduce four novel aspects. First, the temporal and spatial distribution properties of carbon emissions have been drawn. Second, the variables of the spatial econometric model were chosen using the benchmark model to enhance the logic and dependability. Third, considering the presence of spatial correlation, this study used a dynamic spatial Durbin model to examine the effects of digitalization, technical progress, financial development, industrial structure, economic growth, and energy intensity on carbon emissions. Both the short-term and long-term direct and spatial spillover impacts of the factors are examined. Fourth, this study has separated the sample provinces into three groups in order to account for the spatial heterogeneity of various regions.

Research Hypotheses
The process of digitalization has a dual impact on carbon emissions. On one hand, it promotes carbon emissions through increased usage. On the other hand, it inhibits carbon emissions through substitution. However, the rebound effect complicates the overall impact and makes it ambiguous. There is an increasing amount of pertinent research on China demonstrates in terms of direct effects, digitalization is beneficial to reducing carbon emission levels. Digitalization breaks down geographic areas and can have spillover effects on adjacent regions.

Hypothesis 1: *The impact of digitalization on carbon emissions has both direct and spatial spillover effects.*

Digital development has network externalities. As digitalization continues to evolve, the knowledge, information, and technology shared between digital platforms can greatly facilitate technological innovation, thus creating more shared information and technology, creating "positive feedback" and rolling cumulative effect. The continuous development of digitalization accelerates the adoption of green emission reduction technology, and at the same time facilitates the generation of innovative technology, further promotes carbon emission reduction at a higher technical level, and forms a circular cumulative effect.

Hypothesis 2: *Digitalization has a cyclical accumulation effect on carbon emissions, with its long-term influence on emission reduction being stronger than its short-term effect.*
Digital regional heterogeneity affects the impact of carbon emissions. The main factor that leads to carbon emissions is the industrial sector. China's eastern, central, and western regions exhibit notable disparities in their levels of industrial development: the highly industrialised east region has the highest emissions, the central region has considerably lower emissions, and the underdeveloped west region has the lowest carbon emissions. Also, the eastern region reveals superior economic development, improved living conditions, and greater expeditious implementation of diverse low-carbon emission reduction technologies. Furthermore, because of the increased amounts of carbon emissions, local governments have more urgent task of emission reduction. Due to its economic strength, there is also financial support for enterprises to transform and upgrade their industrial structure and adopt low-carbon emission reduction technologies.

Hypothesis 3: *The heterogeneity consequences of digitalization for carbon emissions vary in different locations of China. The greatest impact is in the east area, the second is in the central area and the lowest is in the western area.*

Research Method

Variable Selection

The dependent variable is the carbon emissions, while the independent variable is digitalization. Referring previous research (Myovella et al., 2020; Tchamyou et al., 2019), this article employs internet penetration as a metric to gauge the level of digitalization. Specifically, digitalization is calculated by the equation:

$$Digitalization = (Number\ of\ internet\ users/Total\ population) \times 100\%$$

GDP and GDP2 are control variables (Lin and Zhou, 2021; Wang et al., 2020). GDP is gross domestic product per capita. The GDP series have been converted to 2001 prices to account for the effects of variations in general price levels. Based on the previous analysis, financial development, industrial structure, technology progress (Benjamin and Lin, 2020) and energy consumption are also selected as explanatory variables in this article (Wang et al., 2020). Finance development is determined by the balance of deposits and loans of financial institutions. Industrial structure is employed by the relative share of the secondary industry within the overall industrial composition. R&D investment intensity serves as a proxy variable to quantify technical progress. Energy consumption is defined as the aggregate amount of energy used.

Statistical Description

This study examines provincial panel data of China spanning the years 2001 to 2018. In 2001, computers and the internet further permeated every facet of personal life and commercial applications, as the process of informatization expanded across all fields and industries. China's digital economy ranked as the second largest globally starting in 2018. Furthermore, the economic data in 2019 may be significantly skewed in the results due to the COVID-19 pandemic. Thus, this paper chooses the sample data cut-off year to be 2018. Tibet is omitted because of the significant dearth of data. Data are obtained from China Statistical Yearbook, China Energy Statistical Yearbook and China Environmental Yearbook.

Table 1
Statistical description

Variable	Definition	Obs	Mean	Standard Deviation	Min	Max
LnCDE	Carbon emission	540	2.715	1.696	0.179	8.902
dig	Digitalization	540	0.292	0.183	0.019	0.977
LnGDP	Per capita GDP	540	1.564	0.751	0.253	4.825
LnFin	Finance development	540	1.702	0.624	0.113	5.527
LnSTR	Industrial structure	540	0.431	0.085	0.278	0.803
LnRD	R&D capital investment	540	1.554	1.031	0.019	5.673
LnEne	Energy consumption	540	2.972	1.402	1.064	9.827

Results and Discussion

Benchmark Model Results

To enhance the logical and reliability of the spatial econometric model, the benchmark model is utilised to evaluate the suitability of the variables to be chosen. For comparative analysis purposes, Ordinary least squares (OLS), generalized least squares (GLS), generalized moment estimation (system GMM and differential GMM) techniques are used for evaluating the models's robust, considering nonspatial effects. The OLS regression results listed in Table 2. R-squared is 0.8274, suggesting that our models are well adjusted.

In the presence of endogeneity and heterogeneity, the estimation results obtained using the OLS method will be biased (Majeed, 2018). The endogenous caused by the omission of explanatory variables and the heterogeneity from inter-provincial differences will all lead to biased estimation results. In order to solve these problems, an estimation method, Generalized Moment Estimation (GMM), is applied. In the presence of heterogeneity and endogeneity, finding reasonable instrumental variables, GMM can provide effective and consistent results (Arellano and Bond, 1991). Using the lagged term of the dependent variable (carbon emissions) as an instrumental variable avoids biased estimation (Weeks and Yudong, 2003). In order to evaluate the effectiveness of the selected instrumental variables, this article adopted an over identification test (Hausman and Taylor, 1981). According to AR (2), instrumental variables are exogenous. The results of GMM in Table 2 are consistent estimation results.

Table 2
The estimation result of the basic model

Variable	OLS	GLS	system-GMM	differential - GMM
LnCDE2it-1			0.771*** (5.465)	0.560*** (9.336)
dig	-0.442*** (4.834)	-0.229*** (4.581)	-0.536*** (3.559)	-0.317** (2.442)
LnGDP	1.013** (2.601)	0.542* (1.834)	0.545** (2.302)	0.547** (2.051)
LnGDP2	-0.088** (2.247)	-0.019* (1.729)	-0.029* (1.818)	-0.110** (2.532)
LnFin	0.027*** (2.871)	-0.019* (1.853)	-0.017** (2.191)	-0.013** (2.176)
LnSTR	0.112* (1.736)	0.104** (2.139)	0.235*** (4.711)	0.263*** (6.396)
LnRD	-0.328** (2.214)	-0.017* (1.912)	-0.155* (1.703)	-0.093** (2.107)
LnEne	1.102** (2.085)	0.903*** (5.461)	0.989*** (4.874)	0.790*** (5.987)
Cons	0.771* (1.949)	0.629*** (4.877)	0.872*** (5.215)	0.502*** (4.643)
AR (2)			1.324 (0.416)	0.813 (0.824)
R^2	0.8274	0.8156	0.8297	0.8902
Hansen test			21.91 (0.199)	18.53 (0.973)
Wald test		1378.65***	16645.47***	25761.19***
N	540	540	540	540

Notes：The ***, **, and * indicate significance at the 1%, 5%, and 10% levels. Standard errors in parentheses. Same as below.

Spatial Model Results

1. The temporal - spatial distribution characteristics

Moran's I index are employed to evaluate the spatial autocorrelation of carbon emissions and digitalization, concerning the geographic distance weight matrix. Table 3 reports the Moran's I indexes of carbon emissions and digitalization. The Moran's I statistic demonstrates a statistically significant positive value, thereby rejecting the null hypothesis that there is no spatial autocorrelation. Therefore, carbon emissions and digitalization have significant spatial autocorrelation. The spatial econometric model is suitable. Furthermore, it is not feasible to decrease carbon emissions in a standalone manner; the entity in charge of regulating carbon emissions should implement policies and methods for regional integration management.

To examine the spatial clustering patterns of carbon emissions and digitalization, Moran scatterplots were created for the years 2001 and 2018. Figure 1 shows that in both 2001 and 2018, the majority of provinces had carbon emissions that were cluster in the first quadrant. In 2018, the spatial concentration of carbon emissions is more closely restricted compared to 2001. A possible reason is that the carbon emissions of the 30 provinces in 2018 were higher

than those of 2001, thus showing that the high carbon emission provinces have spatial agglomeration.
Figure 2 shows the Moran scatterplots of the digitalization for 2001 and 2018. These indicate that the digitalization' spatial agglomeration has changed in recent years with more provinces situated in the first quadrant and the Moran scatter plots becoming more diffuse. This implies that there are stronger spatial agglomeration characteristics in the local scope, as more provinces turn from low-low aggregation characteristics to high-high aggregation characteristics. The primary cause is the rapid advancement of digitalization from a minimal to an extensive level in China. Digitalization infrastructure is becoming more widely distributed, the shared characteristics of digitalization are more significant, and digitalization between regions is more closely connected. Moreover, in order to intuitively illustrate the distribution of China's carbon emissions, the provincial levels in 2001, 2006, 2012, and 2018 are illustrated in Figure 3.

Table 3
The spatial correlation test results

Year	Carbon emissions		Digitalization	
	I	Z-values	I	Z-values
2001	0.183***	3.091	0.133***	2.546
2002	0.178***	3.092	0.140***	2.575
2003	0.174***	3.091	0.151***	2.701
2004	0.166***	3.122	0.164***	2.812
2005	0.173***	3.121	0.159***	2.743
2006	0.158***	3.122	0.162***	3.659
2007	0.160***	3.151	0.171***	3.717
2008	0.164***	3.152	0.183***	3.633
2009	0.158***	3.151	0.195***	3.804
2010	0.160***	3.182	0.203***	3.754
2011	0.156***	3.181	0.217***	3.698
2012	0.157***	3.182	0.215***	3.736
2013	0.159***	3.201	0.216***	3.815
2014	0.153***	3.212	0.212***	3.762
2015	0.152***	3.211	0.224***	3.606
2016	0.156***	3.242	0.237***	3.721
2017	0.151***	3.241	0.236***	3.765
2018	0.150***	3.242	0.240***	3.815

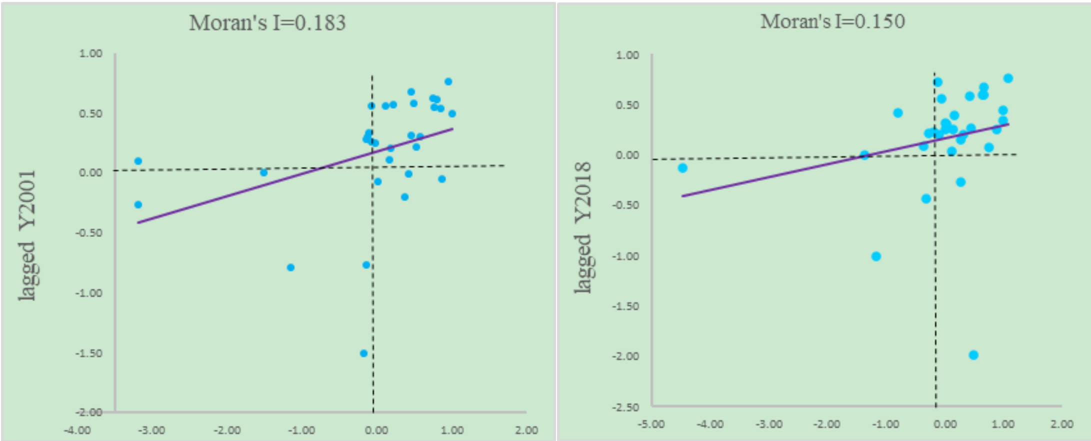

Figure 1. Scatter plot of the Moran's index of China's carbon emissions in 2001 and 2018

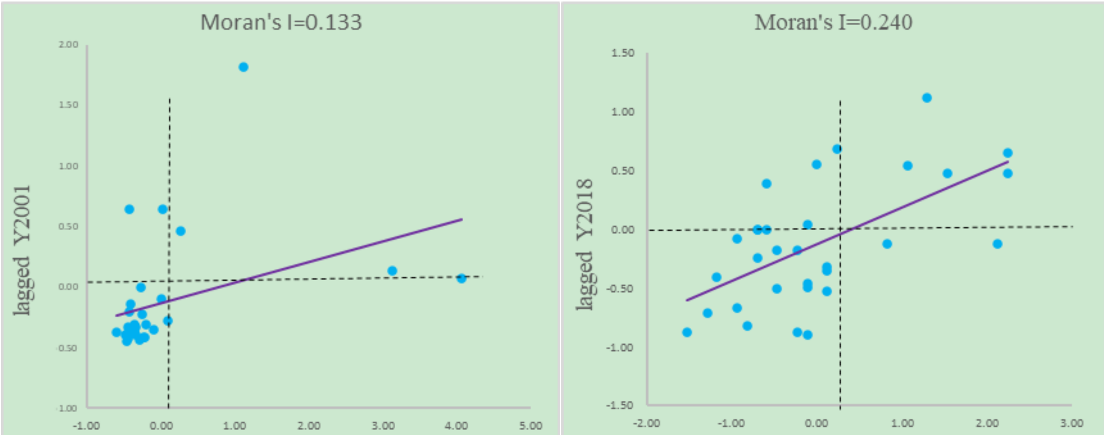

Figure 2. Scatter plot of the Moran's index of China's digitalization in 2001 and 2018

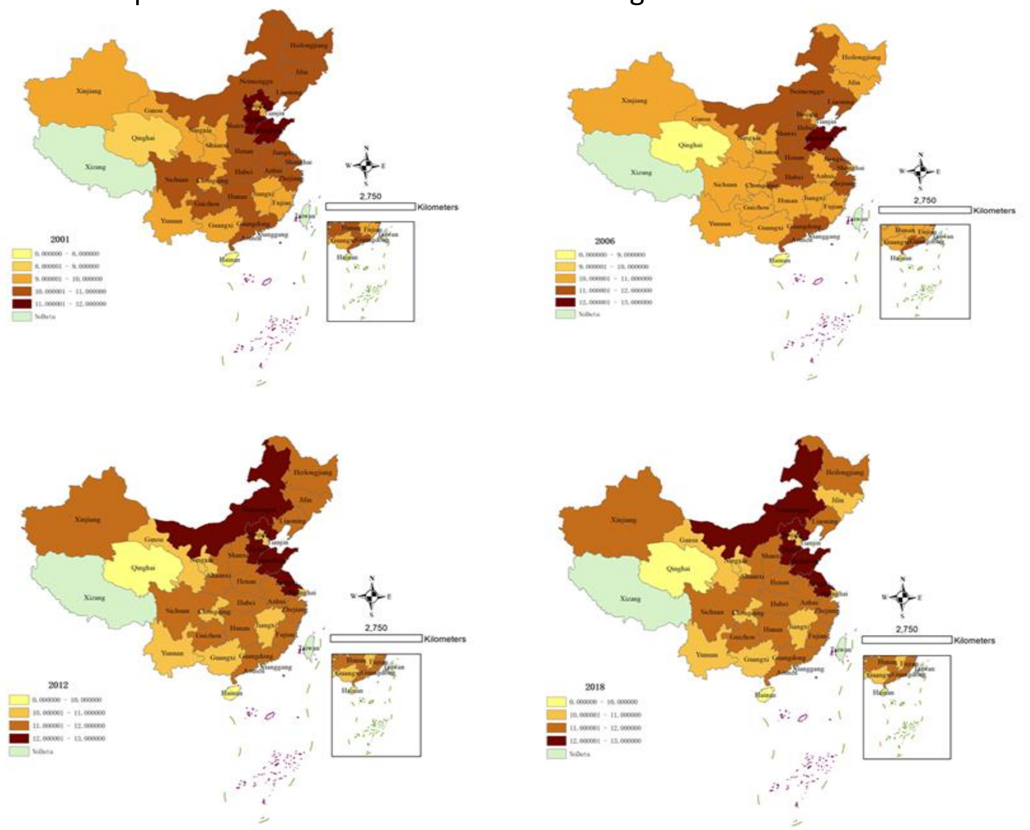

Figure 3. The spatial distribution of China's carbon emissions in 2001, 2006, 2012, 2018

2. Estimation of non-spatial panel models

General panel models do not take into account the impact of geographical elements. In order to select and confirm an appropriate spatial econometric model, several tests must be applied. Table 4 shows the Lagrange multiplier (LM) and the Robust Lagrange multiplier (RLM) lag test pass the robustness test and error tests significantly which means the null hypothesis (no spatial lag and no spatial autocorrelation error term) is rejected. As a result, it is necessary to construct a spatial econometric model to do the research in this paper.

The spatial lag model (SLM) and the spatial error model (SEM) are special forms of the spatial Durbin model (SDM) (Elhorst, 2014). In Table 5, this study used the Wald test and the likelihood ratio (LR) test to check spatial, time, and two-way fixed effects models. The results show there is no spatial lag and no spatial error autocorrelation. The SDM is more suitable than the SEM and the SLM.

Table 4

The estimation result of non - spatial panel model

Variables	No fixed effects	Spatial fixed effects	Time fixed effects	Two-way fixed effects
LnCDE2it-1	0.4162***	0.2214*	0.5376**	0.3139***
	(3.403)	(1.763)	(2.501)	(3.723)
dig	-0.4162**	-0.2214*	-0.3376**	-0.5139**
	(2.423)	(1.874)	(2.171)	(2.167)
LnGDP	0.7162*	0.9214*	0.5376**	0.6139***
	(1.693)	(1.831)	(2.181)	(3.561)
LnGDP2	-0.0162**	-0.0214*	-0.0376*	-0.0139**
	(2.303)	(1.752)	(1.881)	(2.103)
LnFin	-0.0162**	-0.0214*	-0.0376**	-0.0139**
	(3.603)	(1.758)	(2.143)	(3.125)
LnSTR	0.0162**	0.0214	0.0376**	0.0139**
	(2.153)	(1.558)	(2.175)	(2.006)
LnRD	-0.0162**	-0.0214*	-0.0376**	-0.0139***
	(3.493)	(1.658)	(2.161)	(3.364)
LnEne	0.0162***	0.0214*	0.0376**	0.0139***
	(3.423)	(1.958)	(2.144)	(4.762)
Log-likelihood	50.391	376.272	61.895	428.609
LM lag test	52.388***	14.896***	40.032***	0.570
Robust LM lag test	49.824***	0.097	42.941***	1.002
LM error test	3.671*	34.940***	0.834	0.001
Robust LM error test	1.125	20.141***	2.743*	0.621

Table 5
The spatial model diagnosis result

Variables	Spatial fixed effects	Time fixed effects	Two-way fixed effects
Wald spatial lag test	85.439***	127.223***	90.225***
LR spatial lag test	83.637***	97.018***	80.512***
Wald spatial error test	55.937***	161.708***	90.706***
LR spatial error test	55.719***	132.702***	81.027***

3. Estimation of dynamic spatial Durbin model

The dynamic SDM results are presented in Table 6. Based on R2 and log-likelihood, the the two-way fixed effects SDM is more suitable. The results of the explanatory variables align with the benchmark model, indicating that the estimation results are stable.

First, from the coefficient estimation results, the impact of digitalization on carbon emission is significantly negative, indicating that it can effectively alleviate carbon emission levels. It demonstrates that the impact of digitalization on carbon emissions is primarily driven by the substitution effect, resulting in a significant reduction in carbon emission levels. Since 2012, when the Chinese government introduced the concept of green development, it has implemented various measures to promote and facilitate the modernization and improvement of businesses, as well as to achieve a decrease in carbon emissions through the advancement of industrial Internet, energy Internet, and green credits.

Second, the coefficient estimation results of W* DIG demonstrate that digitalization has spatial spillover effects on carbon emissions. Digitalization not only benefits the reduction of carbon emissions in a single location, but also helps to prevent carbon emissions in neighbouring regions. Digitalization is not restricted by geographical administrative regions in terms of the characteristics of receiving and transmitting information so that its development in one region region promotes the development of digitalization in neighboring regions (Wang et al., 2020). Through the utilisation of digital technology, adjacent regions can rapidly acquire and replicate the low-carbon and emission-reducing production techniques employed by neighbouring regions. Hence, digitization has a substantial and beneficial influence on carbon emissions, resulting in notable spatial spillover effects. This could confirm ***hypothesis 1***.

Table 6
The estimation result of dynamic SDM

Variables	No fixed effects	Spatial fixed effects	Time fixed effects	Two-way fixed effects
LnCDE2it-1	0.331*** (3.562)	0.517** (2.455)	0.413** (2.372)	0.522*** (5.963)
dig	-0.216*** (3.274)	-0.411 (1.553)	-0.228** (2.165)	-0.333** (2.465)
LnGDP	0.523*** (3.327)	0.717* (1.856)	0.431 (1.048)	0.528*** (4.717)
LnGDP2	-0.246** (2.035)	-0.321* (1.958)	-0.127 (0.432)	-0.233** (2.326)
LnFin	-0.147** (2.542)	-0.095* (1.753)	-0.223* (1.901)	-0.254*** (5.142)
LnSTR	0.316** (2.019)	0.521 (0.258)	0.337** (2.254)	0.213*** (4.831)
LnRD	-0.116*** (3.836)	-0.081 (1.151)	-0.097** (2.359)	-0.113*** (5.253)
LnEne	0.816** (2.058)	0.721* (1.848)	1.037** (2.176)	0.913*** (3.485)
W*LnCDE2it-1	0.026 (0.361)	0.011 (0.758)	0.037 (1.413)	0.013 (1.437)
W*dig	-0.009** (2.182)	-0.021* (1.868)	-0.036** (2.277)	-0.039*** (5.319)
W*LnGDP	0.116 (0.825)	0.221* (1.538)	0.336** (2.713)	0.213** (2.026)
W*LnGDP2	-0.012 (0.363)	-0.001* (1.328)	-0.037** (2.522)	-0.010 (0.548)
W*LnFin	-0.026** (2.452)	-0.041 (1.458)	-0.077** (2.234)	-0.039** (2.273)
W*LnSTR	-0.072 (0.547)	-0.094 (1.508)	-0.076** (2.328)	-0.059** (2.291)
W*LnRD	-0.116** (2.012)	-0.094 (1.238)	-0.136** (2.177)	-0.219* (1.845)
W*LnEne	0.512 (0.423)	0.721* (1.678)	0.836** (2.165)	0.613** (2.132)
W*LnCDE2it	0.0162 (0.136)	0.0214* (1.818)	0.0376** (2.236)	0.0139* (1.774)
R^2	0.8702	0.9013	0.9133	0.9256
Log-likelihood	107.91	425.34	129.47	469.21

4. Estimation result of decomposition effects

Explanatory variables exhibit significant effects on carbon emissions when considering both short-term and long-term decomposition effects. First, in the short and the long term, the direct, indirect,and total effect of digitalization on carbon emissions are significantly negative. From the standpoint of the decomposition effect, the impact of digitalization on carbon emissions is mostly driven by the substitution effect, which is more influential than the use effect. Digitalization plays a significant role in mitigating carbon emissions. Second, the indirect impact of digitalization on carbon emissions is greater than the direct effect in both the short and long term, suggesting the existence of a feedback mechanism (Wang and Li, 2019). The impact of digitalization on carbon emissions has repercussions for neighbouring regions, and the effect on the adjacent areas is passed back to the original area. Third, the long-term direct effect is stronger than the short-term direct effect, the long-term indirect effect is stronger than the short-term indirect effect, the long-term total effect is stronger than the short-term total effect. This implies digitalization has a cumulative effect on carbon emissions (Zheng et al., 2023). These could confirm ***hypothesis 2***.

Table 7
The estimation result of decomposition effects

Variable	Short-term Direct effect	Indirect effect	Total effect	Long-term Direct effect	Indirect effect	Total effect
dig	-0.114*** (3.251)	-0.221* (1.775)	-0.335** (2.467)	-0.223*** (6.759)	-0.449*** (4.093)	-0.672*** (3.534)
LnGDP	0.416*** (3.527)	0.321 (1.414)	0.737** (2.372)	0.713*** (3.736)	0.514** (2.044)	1.227*** (3.357)
LnGDP2	-0.012** (2.163)	-0.026 (1.323)	-0.038** (2.196)	-0.043 (0.773)	-0.017** (2.033)	-0.060* (1.735)
LnFin	-0.116** (2. 078)	-0.094 (1.351)	-0.210** (2.733)	-0.331* (1.827)	-0.257** (2.065)	-0.588** (2.384)
LnSTR	0.212*** (3.814)	0.091* (1.736)	0.303** (2.021)	0.293** (2.163)	0.119** (2.023)	0.412** (2.267)
LnRD	-0.196*** (4.202)	-0.221*** (2.749)	-0.417** (2.265)	-0.314*** (3.711)	-0.448*** (5.047)	-0.762*** (4.233)
LnEne	0.716*** (3.926)	0.114** (2.363)	0.830** (2.432)	1.013** (2.423)	0.117** (2.016)	1.130*** (5.695)

5. Regression analysis of regional heterogeneity

To assess regional heterogeneity, this section categorizes the study samples into three regions: eastern, central, and western. The following conclusions can confirm ***hypothesis 3***. First, in eastern China, the impact of digitalization on carbon emissions is significantly negative in the short and long term. From the regional perspective, the eastern region exerts the most significant influence on carbon emissions, with the central region and the western region following suit. There are several potential reasons for this phenomenon: Primarily, in terms of magnitude, the primary contributor to carbon emissions is the manufacturing industry. The level of industrialization varies significantly among the eastern, central, and western regions of China. The eastern region exhibits the highest level, followed by the centre region and then the western region. Regional carbon emissions also follow the same order. Undoubtedly, digitization has a pronounced impact on reducing carbon emissions in the eastern region, although its influence on carbon emission reduction in the western region is comparatively smaller. Furthermore, at a technical level, the eastern region exhibits a superior degree of economic progress, improved living standards, and a faster implementation of diverse low-carbon emission reduction technologies. Furthermore, because of the elevated carbon emission levels in the eastern region, the local government is faced with a more pressing

responsibility to decrease emissions. Due to its greater economic strength, there is more financial support for enterprises to transform and upgrade their industrial structure and adopt low-carbon emission reduction technologies.
Second, the impact in the eastern and central regions is notably greater than in the western region, although the indirect effect in the western region surpasses that in the eastern and central regions. This suggests that the eastern region possesses the most robust autonomous ability to decrease carbon emissions through digitalization, while the western region is more dependent on the surrounding regions for this issue. The possible explanations for this are as follows: On the one hand, the national emission reduction tasks have been issued due to the elevated level of carbon emissions in eastern China, resulting in greater pressure on local governments to reduce emissions. Therefore, more stringent emission reduction measures need to be introduced, and the subjective motivation for emission reduction is stronger. On the other hand, the eastern China exhibits a greater degree of economic advancement, enabling local governments to possess a larger pool of financial resources for the purpose of promoting and facilitating the modernization and enhancement of firms, as well as augmenting the adoption of emission reduction technologies, in order to achieve better carbon emission targets. In the western region, the carbon reduction base is small, and local governments have little financial support, leading to a lack of motivation to reduce emissions.
Third, whether in the eastern, centre or western regions, the long-term direct effects have increased. It is evident that various regions are increasingly embracing digitalization as a means to decrease carbon emissions. Moreover, there is a growing emphasis on leveraging digitalization to attain this objective. The possible explanation for this is that climate change and environmental issues have received considerable attention in recent years, whether from the government, enterprises or individuals, and there has been growing awareness of environmental protection, low-carbon production and low-carbon lifestyles.

Table 8
The estimation result of decomposition effects in the eastern region

Variable	Short-term Direct effect	Indirect effect	Total effect	Long-term Direct effect	Indirect effect	Total effect
dig	-0.126***	-0.341***	-0.467***	-0.593**	-0.919**	-1.512***
	(5.275)	(4.352)	(3.545)	(2.004)	(2.246)	(7.353)
LnGDP	0.316**	0.221*	0.537**	0.413**	0.316**	0.729***
	(2.534)	(1.757)	(2.346)	(2.187)	(2.072)	(4.837)
LnGDP2	-0.014*	-0.021*	-0.035**	-0.023	-0.049**	-0.072**
	(1.787)	(1.653)	(2.444)	(0.543)	(2.025)	(2.416)
LnFin	-0.116***	-0.124**	-0.240***	-0.418***	-0.313**	-0.731***
	(5.842)	(2.157)	(4.948)	(3.128)	(2.188)	(6.784)
LnSTR	0.315	0.121*	0.436	0.519	0.117	0.636
	(0.769)	(1.754)	(1.343)	(0.392)	(0.205)	(0.473)
LnRD	-0.312***	-0.524*	-0.836**	-0.513***	-0.817**	-1.330***
	(3.548)	(1.756)	(2.042)	(3.229)	(2.313)	(3.595)
LnEne	-0.716	-0.321	-1.037	-0.913	-0.719	-1.632
	(0.051)	(1.254)	(0.649)	(0.011)	(0.209)	(0.637)

Table 9
The estimation result of decomposition effects in the central region

Variable	Short run Direct effect	Indirect effect	Total effect	Long run Direct effect	Indirect effect	Total effect
dig	-0.096** (2.156)	-0.224* (1.851)	-0.330** (2.727)	-0.315** (2.359)	-0.617* (1.885)	-0.932*** (3.974)
LnGDP	0.011** (2.172)	0.026* (1.947)	0.037** (2.369)	0.039* (1.721)	0.047** (2.236)	0.086** (2.329)
LnGDP2	-0.002 (0.131)	-0.021 (0.262)	-0.023 (1.132)	-0.031 (0. 902)	-0.047 (0.824)	-0.078 (0.563)
LnFin	-0.1156* (1.697)	-0.081* (1.779)	-0.196** (2.278)	-0.301* (1.938)	-0.374** (2.396)	-0.675** (2.007)
LnSTR	0.212** (2.048)	0.055* (1.734)	0.267** (2.136)	0.418** (2.383)	0.103* (1.821)	0.522** (2.135)
LnRD	-0.046*** (3.584)	-0.224* (1.726)	-0.270** (2.414)	-0.213* (1.877)	-0.717** (2.557)	-0.930** (2.686)
LnEne	0.522* (1.825)	0.021* (1.683)	0.543* (2.593)	1.015** (2.146)	0.039 (0.043)	1.054** (2.423)

Table 10
The estimation result of decomposition effects in the western region

Variable	Short-term Direct effect	Indirect effect	Total effect	Long-term Direct effect	Indirect effect	Total effect
dig	-0.002* (1.659)	-0.014* (1.705)	-0.016** (2.034)	-0.115* (1.946)	-0.413* (1.827)	-0.528** (2.235)
LnGDP	0.214* (1.802)	0.021* (1.911)	0.235 (0.076)	0.318 (0.217)	0.055 (0.029)	0.373 (0.108)
LnGDP2	-0.011 (0.374)	-0.004 (1.323)	-0.015 (0.082)	-0.019 (1.104)	-0.013 (1.344)	-0.032 (0.473)
LnFin	-0.044* (1.847)	-0.021* (1.726)	-0.065 (0.467)	-0.236* (1.659)	-0.027 (0.798)	-0.263 (0.836)
LnSTR	0.312* (1.795)	0.124* (1.949)	0.436** (2.029)	0.513* (1.923)	0.219** (2.245)	0.732*** (2.574)
LnRD	-0.001* (1.766)	-0.003 (0.577)	-0.004* (1.846)	-0.059** (2.038)	-0.117* (1.856)	-0.176** (2.457)
LnEne	0.021* (1.821)	0.004 (1.432)	0.025** (2.395)	0.032** (2.271)	0.019* (1.717)	0.051** (2.193)

Conclusions and Suggestions

Based on extensive empirical research, the following are the main findings.

First, the time-spatial distribution of carbon emissions has been visualized. As carbon emissions in China continue to rise, an increasing number of provinces are exhibiting high levels of concentration, and over time, the geographical concentration among provinces is becoming more pronounced.

Second, the effect of digitalization on carbon emissions is predominantly negative, suggesting that the substitution effect of digitalization on carbon emissions outweighs the use effect. Furthermore, digitalization has a substantial adverse spatial spillover effect on carbon emissions. This means the impact is not only advantageous for reducing carbon emissions in a particular area, but also Contributes to the mitigation of carbon emissions in nearby regions.
Third, the impact of digitalization on carbon emissions is mostly driven by the substitution effect, which outweighs the use effect. The impact of digitalization on carbon emissions is stronger in both the short and long term when considering indirect effects rather than direct effects, suggesting the presence of a feedback mechanism. In addition, when comparing short-term and long-term trends, it is evident that the long-term direct effect surpasses the short-term direct effect, the long-term indirect influence is more pronounced than the short-term indirect effect, and the long-term overall effect is more powerful than the short-term total effect. This indicates that the process of digitization has a compounding impact on carbon emissions.
Forth, based on the projected findings in eastern China, digitalization has a notably adverse influence on carbon emissions. Also, the direct and indirect effects are larger in eastern China compared to the national average. When comparing different regions, it is evident that the eastern region has the most significant influence on carbon emissions, followed by the central region and then the western region. The eastern region, characterised by the greatest carbon emission base, advanced emission reduction technology, and greater financial support, experiences the most significant impact of digitalization on carbon emissions. The direct influence is more pronounced in the eastern and central regions compared to the western region, whereas the indirect effect is more pronounced in the western region compared to the eastern and central regions. These findings suggest that the eastern area has the highest level of self-sufficiency in reducing carbon emissions through digitalization, whereas the western region relies more on neighbouring regions.
Besides, this shows that the autonomy of all regions in using digitization to reduce carbon emissions is increasing, and all regions are paying greater attention to using digitalization to reduce carbon emission levels. In recent years, climate change and environmental issues have attracted significant attention. The government, enterprises and individuals have become increasingly aware of the need for environmental protection, low-carbon production modes and low-carbon lifestyle.
Based on the findings, the study suggests several practical and pertinent policy implications:
First, it is important to implement regional collaboration and control measures to effectively reduce carbon emissions, considering the spatial agglomeration characteristics of these emissions. Government should consider implementing ecological compensation and interest coordination mechanisms to address local carbon emission. Creating a standardised framework for exchanging and tracking data on carbon emissions would be advantageous, as well as strengthen regional collaboration in enforcing environmental laws. By doing so, a collective effort can be formed to effectively control carbon emissions in the region.
Second, policy makers should possess a long-term perspective when discussing low-carbon development strategies and policies aimed at reducing carbon emissions. The advancement in digitalization technology and the expansion of financial systems have substantial impacts on reducing carbon emissions. These effects are compounded over time, resulting in long-term benefits. In order to expedite the process of transforming and improving a province's industrial structure and optimising its energy consumption, it is imperative to replace fossil fuels with cleaner alternatives like solar and wind energy. The industrial structure and energy

consumption of a province tend to have a significant level of resistance to change. Promoting digital development is of great importance and necessary to facilitate industrial upgrading. Enabling the transfer of technology will stimulate the dissemination of technological innovations and aid in the mitigation of carbon emissions.
Third, Authorities must optimise the aim for reducing carbon emissions and develop assessment measures that integrate storage and augmentation. It is imperative to not only decrease the current level of carbon emissions, but also to concern about carbon storage. Furthermore, the western region exhibits a deficiency in both motivation and willingness to decrease emissions. Therefore, the western region needs more financial and technical support to gradually reduce emissions and encourage the achievement of low carbon emission policy objectives. In addition, it is imperative to further enhance the environmental consciousness of local authorities, businesses, and individuals. This entails promoting low-carbon production methods and lifestyles, as well as fostering greater enthusiasm and initiative towards reducing carbon emissions.

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