ASSESSING THE SPATIAL EFFECT OF DIGITAL INFRASTRUCTURE INVESTMENT ON THE GREEN DEVELOPMENT OF THE MANUFACTURING SECTOR IN CHINA

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(Received 22nd Apr 2025; accepted 16th Jun 2025)

Abstract. The Chinese government established the objectives of achieving "carbon peaking" by 2030 and reaching "carbon neutrality" by 2060. Digitization of the manufacturing sector is an important means of reducing carbon emissions, and accelerating the construction of digital infrastructure is an important impetus to improve resource allocation efficiency. Using panel data from 30 provinces in China during the research period from 2007 to 2021, this research analyzes the spatial spillover effect of digital infrastructure investment on the green development of the manufacturing sector from the perspective of its digital transformation within the sector. The results indicate that digital infrastructure investment fosters green development within the local manufacturing sector, and also significantly enhances the green development in neighboring regions through a spatial spillover effect, which exhibits notable geographical boundaries. Further analysis reveals that digital infrastructure investment primarily promotes green development by facilitating technological progress, yet it may also inhibit green development by widening the technology gap.
Keywords: *digital infrastructure investment (DII), green development of manufacturing sector, spatial spillover effect (SSE), carbon peaking and carbon neutrality, technological progress and technology gap*

Introduction

After the development of recent decades, the technical level and scale of China's manufacturing sector have achieved great achievements, which is of great significance to China's economic development (Xu et al., 2023a). However, China's economy also faces with many dilemmas, such as vanishing demographic dividend, excess production capacity, and reduced added value of products (Wan and Lee, 2023). The advancement of a new generation of digital technologies, including cloud computing, big data, blockchain, artificial intelligence, and the Internet of Things, is propelling the digital transition and upgrading of the global manufacturing sector, offering opportunities for the manufacturing sector to overcome the challenges it faces (Liu et al., 2023). As the Chinese government promotes the big data strategy, digital technology is gradually emerging as a fresh impetus for China's economic development, and the importance of digital infrastructure construction is becoming increasingly prominent. Digital infrastructure is a novel style of infrastructure with intellectual property or digital technology as the core value, which is the "information highway" for data flow and constructs a new productivity structure and social production relations, and digital infrastructure construction is indispensable for deepening the digital transition (Li and Yang, 2021; Liu and Tian, 2023). The digital infrastructure construction can promote technological transformation and

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2304_81318148

drive the digital transition of the traditional manufacturing sector (Jacob et al., 2023; Li et al., 2023). So what is the impact of *DII* on green development in China's manufacturing sector? What is the action mechanism? It is of great practical value and theoretical significance to investigate this problem deeply for the digital transition of the manufacturing sector and the optimization of resource allocation efficiency. The positive influence of digital technology on total factor productivity (*TFP*), optimization of labor employment structure, poverty alleviation development, narrowing urban-rural gap, and global value chain climbing have already appeared (Wen et al., 2022; Chen et al., 2022; Jia, 2024).

Some literature also put forward that China's economic development is affected by telecommunications infrastructure, and the fast expansion of the Internet has become a new driving force to improve regional innovation efficiency (Tang et al., 2022). However, the influence of DII on green development is controversial (Xu et al., 2023b). Digital technology is changing the commercial mode of energy supply and transforming the pattern of energy consumption (Arachchi and Managi, 2021). Although the enhancement of energy efficiency cuts carbon emissions to some extent and promotes green development, the increase in energy services may increase carbon emissions (Zhang et al., 2023; Xie et al., 2023). The manufacturing sector is the foundation of China's national economy and a major emitter of carbon emissions, and there is an increasing focus on how to realize green development and cut carbon emissions.

According to the above literature analysis, this research employs a panel dataset covering 30 provinces in China during the research period from from 2007 to 2021 as samples to study the *SSE* of *DII* on the green development of China's manufacturing sector and its geographical boundaries.

Compared with previous literature, the contribution of this research is as follows. First, from the viewpoint of the digital transition of the manufacturing sector, the economic impact of *DII* is investigated, which provides a theoretical basis for digital development strategy. Secondly, from the digital perspective, the spatial Dubin model is applied to identify and measure *SSE* and the geographical boundary of *DII* on green development within China's manufacturing sector, which is beneficial for enhancing the development of a green economic system. Thirdly, starting from the mechanism of digital transition, it is proposed that *DII* can promote green development by influencing technological efficiency, technological progress, and technological gap, which helps to guide manufacturing sector development.

Literature review

The influence of DII on TFP

Some literature examined the factors influencing TFP from the viewpoint of human capital (Wang et al., 2021), industrial structure (Wang and Wang, 2023), environmental regulation (De Santis et al., 2021), and foreign direct investment (Zaira et al., 2019; Li et al., 2022; Lin and Xie, 2023), etc. Investment in digital infrastructure provides a sustained impetus for economic growth (Chen et al., 2023), not only facilitating efficiency improvements and technological advances leading to higher output (Xi et al., 2022) but also helping to achieve optimal resource allocation (Liu et al., 2022). As a result, digitization has also been cited as a key factor in *TFP* growth (Pan et al., 2022).

However, some scholars presented the opposing viewpoint. Badescu and Garcés-Ayerbe (2009) studied the impact of digitization on labor productivity by using the panel data of Spanish companies, and found that although there was a certain degree of improvement in labor productivity during the investigation time, it was not significant. Acemoglu et al. (2014) found, using the manufacturing data of the United States, that there is not sufficient evidence to verify that digitization improves productivity.

The influence of DII on environmental pollution

Digital technology not only has a certain influence on *TFP* growth but also has a direct or indirect impact on carbon emissions (environmental pollution). Joon and Eungkyoon (2012) thought that digital technology may help cut pollution emissions because it can strengthen supervision to exert psychological pressure on polluters. Salahuddin et al. (2016) argued that digital transition has very little impact on CO_2 emission in the near and may enhance the potential for emission reduction in the future. Digital transition may be the cause of both the rise and the fall of CO_2 emission in a theoretical analysis. Higón et al. (2017) studied the nonlinear between CO_2 emissions and digital transition and found that there is an inverted U-shaped pattern between CO_2 emissions and digital transition. The breakpoint of digital transition in developing countries exceeds the average significantly, while that in developed countries is lower than the average. Ozcan and Apergis (2018) studied emerging countries and found that increasing internet access can reduce air pollution levels.

Green total factor productivity (GTFP) of research

The emissions of pollutants or CO_2 are not the target product of production, but more a by-product. Therefore, some scholars try to include the emission of CO_2 or pollutants in the evaluation of *TFP*. Wang et al. (2023) calculated the *GTFP* of the manufacturing sector and found that *GTFP* was significantly lower than *TFP*. Yu et al. (2022) measured carbon emissions performance employing a non-radial directional distance function (*DDF*) to incorporate CO_2 into the analytical framework. The inefficiencies caused by input-output slack variables are addressed by not considering the same proportional changes in desired and non-desired outputs, making the measurement of *GTFP* more accurate.

However, the above literature assumes that all decision-making units are in the same production frontier, without considering the technological gap between decision-making units. Du et al. (2018) and Cao et al. (2020) employed the modified *GMM* and Malmquist-Luenberger model to solve the issue that decision-making units were in the same production frontier without considering the technical gap of decision-making units. According to the above analysis, this research employs a non-radial *DDF* and a frontier model to measure *GTFP* and describe it as green development.

Based on the above analysis, the contribution of this paper is to integrate *TFP* and carbon emissions into the same research framework, exploring the synergistic effects and interaction mechanisms of digitalization on both economic efficiency and environmental benefits. This paper introduces the analysis of spatial spillover effects, adopting a spatial measurement model to quantify the spillover intensity of digitalization on TFP and carbon emissions in adjacent regions. It further expands the analysis to explore nonlinear relationships and regional heterogeneity. To provide a basis for formulating cross-regional digital policies, promote the coordinated governance of regional economy and environmental protection through optimized resource allocation, establish a policy evaluation system that balances efficiency and environmental protection, and enhance the pertinence of digital policies.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2304_81318148

Models and data sources

Theoretical model

To study the green development of the manufacturing sector and *DII*, this research constructs a theoretical model of the impact of digitalization on economic green development. According to the production model of economic development, this research divides the investment in the production model into digital and non-digital investment, assuming that the model is expressed as:

$$Q/C=f\,(L,\ K_{it},\ K_n,\ E,\ A) \qquad \text{(Eq.1)}$$

where Q represents output, C is CO_2 emissions, L is labor input, K_{it} is digital input, K_n is non-digital input, E is energy input, and A is technical parameters. Q/C is desire output, the larger it is, the higher the desire output is, and vice versa. Under the condition of constant scale returns and effective use of input in the competitive market, the benefit of input to output is the proportion of input in total cost. Assuming that f is the CO_2 function, f is represented in logarithmic form in this study (lowercase letters denote logarithms):

$$q\text{-}c=s_l l + s_{it}k_{it}+ s_n k_n+ s_e e+ \alpha \qquad \text{(Eq.2)}$$

where S represents the share of input variables. Considering the externalities of digitization, the benefit generated by digitalization exceed the factors measured by digitalization, so the proportional term θ representing the externalities of digitalization is increased, hence to obtain the *formula (2)*:

$$q\text{-}c=s_l l + (s_{it}+\theta)\, k_{it} + s_n k_n+ s_e e+ \alpha \qquad \text{(Eq.3)}$$

The factor share that can be observed is S_{it}, and θ cannot be directly observed. According to the definition, *GTFP* represents the disparity between the utilization rate of output and input. Therefore, according to *equation (3)*, the following equation can be obtained:

$$GTFP= q\text{-}\ c\text{-}\ s_l l\ \text{-}\ s_{it}k_{it}\text{-}\ s_n k_n\text{-}\ s_e e= \theta\, k_{it}+ a=\beta_0 IT+ \alpha \qquad \text{(Eq.4)}$$

where α is a technical parameter indicating the level of technology in a specific region. According to the theory of endogenous growth, this research uses a linear function of human capital to represent the technical parameters α:

$$\alpha=\beta_1\mathrm{HUCA}+ \boldsymbol{\varepsilon} \qquad \text{(Eq.5)}$$

where *HUCA* denotes the human capital level of a region, and ε denotes the error term. Then, by incorporating *equation (5)* into *equation (4)*, this paper can obtain the GTFP equation as follows:

$$GTFP= \beta_0 IT+ \beta_1 HUCA+ \boldsymbol{\varepsilon} \qquad \text{(Eq.6)}$$

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2304_81318148

To investigate the impact of other factors on *GTFP*, environmental regulation (*ENRE*), industrial structure (*IS*), energy consumption structure (*ECS*), and foreign direct investment (*FDI*), etc. are taken as control variables, thus *equation (7)* is obtained:

$$GTFP=\beta_0 IT+\beta_1 HUCA+\beta_2 IS+\beta_3 ENRE+\beta_4 FDI+\beta_5 ECS+\boldsymbol{\varepsilon} \quad \text{(Eq.7)}$$

The econometric model for spatial data

The econometric model consists of two basic models, "spatial autoregression (SAR)" and "spatial error model (SEM)". The former introduces spatial factors into the model through spatial lag term. The latter introduces spatial factors into the model through "spatial error term". The SAR model is expressed as:

$$y_{it}=\delta\sum_{j=1}^{N}w_{ij}y_{jt}+\alpha+X_{it}\beta+\mu_i+\lambda_t+\varepsilon_{it} \quad \text{(Eq.8)}$$

where i is the region, t indicates time, y is the "explanatory variable", w is the "spatial weight matrix", $\sum_{j=1}^{N}w_{ij}y_{jt}$ is the "spatial lag term", and δ is the "spatial lag coefficient"; X is the "explanatory variable", β is its coefficient, and ε_{it}, λ_t, and μ_i denote respectively the "random error term", time effect, and spatial effect. The SEM is expressed as:

$$\begin{aligned} \mathrm{y}_{it}&=\alpha+X_{it}\beta+\mu_i+\lambda_t+\varphi_{it} \\ \varphi_{it}&=\rho\sum_{j=1}^{N}w_{ij}\varphi_{jt}+\varepsilon_{it} \end{aligned} \quad \text{(Eq.9)}$$

where φ_{it} is the random error term, $\sum_{j=1}^{N}w_{ij}\varphi_{jt}$ is the "spatial error term", and ρ is the "spatial error coefficient".

In addition, LeSage and Pace (2010) constructed "spatial Dubin model (SDM)" based on the above two models. The basic form of SDM is:

$$y_{it}=\delta\sum_{j=1}^{N}w_{ij}y_{jt}+\alpha+X_{it}\beta+\gamma\sum_{j=1}^{N}w_{ij}X_{jt}+\mu_i+\lambda_t+\varepsilon_{it} \quad \text{(Eq.10)}$$

where $\sum_{j=1}^{N}w_{ij}X_{jt}$ is the "spatial lag term", and γ is its coefficient vector.

Description of variables

Independent variables

GTFP and its decomposition in the manufacturing sector. Fukuyama and Weber (2010) and Zhou et al. (2012), etc. used radial or non-radial *DDF* to measure *GTFP*. Although these models also take into account the change proportion of undesirable and desirable outputs, the accuracy and reliability of the estimated results are improved, but there is a notable flaw, which is that decision-making units are considered homogenous. The flaw leads to the difficulty in correctly reflecting the difference of decision-making units in the measured *GTFP*. Battese and Rao (2004) incorporated group heterogeneity into the traditional "Malmquist-Luenberger index model" to solve this flaw. According to Zhang

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN1785 0037 (Online)
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and Choi (2013) and Cheng et al. (2018), this research employs non-radial *DDF* and the common frontier method to measure *GTFP* in the manufacturing sector. It is further decomposed into the technical progress change index (*TPCI*), technical efficiency change index (*TECI*), and technical gap change index (*TGCI*).

Input and output variables need to be set in advance in the actual calculation process. Input variables consist of energy input, capital input, and labor input. Energy input is quantified by the total energy consumption of the manufacturing sector; the capital input adopts the fixed assets investment of the manufacturing sector in the corresponding year, which is accounted as stock by the "perpetual inventory method"; the labor input is the number of manufacturing employees in China's provinces during the research period from 2007 to 2021. As for output variables which encompass both undesirable and desirable outputs. Among them, the output variables adopt the gross manufacturing product of the province from 2007 to 2021, which is calculated as the constant price based on the 2000 year by using a deflator. For the undesirable outputs, the research obtains the total carbon emissions of the manufacturing sector in the province according to Cheng et al. (2018).

Key dependent variables

The digital infrastructure investment (*DII*). The network communication technology serves as the foundation for the construction of digital infrastructure, which guarantees the operation, storage, and circulation of massive data, and carries out the application of big data, cloud computing, etc. other related technologies based on the above, to establish a diversified digital infrastructure. Therefore, referring to Li et al. (2022), this research employs the ratio of telecom "fixed asset investment" to "total fixed asset investment" to measure *DII*.

Controlled variables

Human capital (*HC*). Innovation has always been regarded as an important factor for the enhancement of *TFP*, and *HC* is the source of innovation. Therefore, this paper takes *HC* as the controlled variable influencing the green development of the manufacturing sector. This paper selects the average years of schooling of the regional population to measure *HC* and calculates the average years of schooling by using the weighted average of the educational background of different populations. The educational background is categorized into elementary school, middle school, high school, and university, and the years of schooling are assumed to be 6, 9, 12, and 16 years, respectively.

Industrial structure (*IS*). The upgrading of *IS* indicates the transformation of capital-intensive to technology-knowledge-intensive industries, which indicates that the traditional industries with low added value, high energy consumption, and high pollution are substituted by those with high added value, low energy consumption, and low pollution, thus reducing energy consumption and improving energy efficiency within the manufacturing sector overall, thus promoting the green development of the social economy. Therefore, this research employs the proportion of high-tech industry-added value to manufacturing industry-added value to measure *IS*.

Environmental regulation (*ER*). *ER* is the intensity of the government's endeavors to control environmental pollution. With the increased intensity of *ER*, manufacturing companies will try to cut CO_2 emissions on the premise of maintaining development, to facilitate the green development of the manufacturing sector. In this paper, the total amount of pollutant discharge fees per unit area of each region is taken as *ER*.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN1785 0037 (Online)
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Foreign direct investment (*FDI*). *FDI* is a significant factor influencing environmental pollution. Regions anticipate that the clean production technology introduced by *FDI* will enhance the local environment. However, *FDI* also introduces energy-intensive companies, which exacerbate carbon emissions. Therefore, *FDI* is also one of the factors affecting the green development of the manufacturing sector. This paper measures *FDI* using the ratio of annual actual utilized foreign investment in *GDP*.

Energy consumption structure (*ECS*). This paper measures *ECS* using the proportion of total coal consumption to total energy consumption, given that coal is the primary energy in China and also a major contributor to environmental pollution, which adversely affects green development (*Table 1*).

Table 1. *Descriptive statistics of variables*

Variables	Sample numbers	Average values	Standard deviation	Minimum	Maximum
ln*GTFP*	450	0.0859	0.2419	-0.8680	0.7958
ln*DII*	450	-3.6769	0.6815	-4.6256	-2.3030
ln*HUCA*	450	2.1520	0.1149	1.7275	2.5006
ln*IS*	450	-2.1736	0.2375	-3.4271	-1.0501
ln*ENRE*	450	-6.6349	0.7529	-9.6058	-4.6137
ln*FDI*	450	-4.2550	1.0727	-7.9489	-1.9648
ln*ES*	450	-0.4389	0.3961	-2.24659	-0.1359

Data sources

Considering the validity and availability of the data, panel data of 30 provinces in China are chosen for analysis. The data came from the China Industrial Statistics Yearbook, China Statistical Yearbook, China Environmental Statistics Yearbook, China Energy Statistics Yearbook, and China Labor Statistics Yearbook during the research period from 2007 to 2021. To reduce heteroscedasticity as far as possible in the regression process, the logarithm of each variable is taken. To avoid the serious multicollinearity problem, the multicollinearity and correlation among variables are tested. The test results indicate that there is no serious multicollinearity (*Table 2*).

Table 2. *Test of correlation and multicollinearity*

	VIF	1	2	3	4	5	6	7
1.ln*GTFP*		1.0000						
2.ln*DII*	2.29	0.1860	1.0000					
3.ln*HUCA*	2.01	0.2129	0.3940	1.0000				
4.ln*IS*	1.60	0.1276	0.2688	0.3531	1.0000			
5.ln*ENRE*	1.69	0.2595	0.3209	0.1058	0.2186	1.0000		
6.ln*FDI*	1.38	-0.0591	0.2018	0.2141	-0.1366	-0.3708	1.0000	
7.ln*ES*	1.30	-0.3588	-0.1281	-0.2538	-0.1889	-0.2604	-0.2331	1.0000

Empirical analysis

Analysis of green development in the manufacturing sector

DII shows that the average *GTFP* during 2007-2021 is 1.0897, which means that the manufacturing sector overall has better achieved green development (*Table 3*).

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2304_81318148

Table 3. *Green development in various regions from 2007 to 2021*

Regions	Provinces	GTFP	TECI	TPCI	TGCI
Eastern region	Beijing	1.1602	1.0503	1.1200	1.0000
Eastern region	Tianjin	1.0588	1.0382	1.1121	1.0000
Eastern region	Hebei	1.1293	1.0304	1.1009	1.0000
Eastern region	Liaoning	1.0715	0.9991	1.1041	1.0000
Eastern region	Shanghai	1.1120	0.9998	1.1121	1.0000
Eastern region	Jiangsu	1.1100	1.0119	1.1101	1.0000
Eastern region	Zhejiang	1.0992	0.9683	1.1102	1.0000
Eastern region	Fujian	1.1221	1.0119	1.0762	1.0000
Eastern region	Shandong	1.1421	1.0339	1.1012	1.0000
Eastern region	Guangdong	1.1011	1.0000	1.1009	1.0000
Eastern region	Hainan	1.0672	0.9562	1.1029	1.0000
Eastern region average value		1.1067	1.0009	1.1046	1.0000
Central region	Shanxi	1.0849	1.0261	1.1201	0.9471
Central region	Jilin	1.0601	1.0383	1.1202	0.9459
Central region	Heilongjiang	0.9888	0.9471	1.1033	0.9689
Central region	Anhui	1.1349	1.0681	1.1198	0.9616
Central region	Jiangxi	1.1161	1.0523	1.0948	0.9881
Central region	Henan	1.0976	1.0000	1.1327	0.9689
Central region	Hubei	1.0846	1.0448	1.1560	0.9571
Central region	Hunan	1.1019	1.0286	1.1114	0.9780
Central region average value		1.0836	1.0256	1.1197	0.9644
Western region	Inner Mongolia	1.0657	1.0526	1.1195	0.9515
Western region	Guangxi	1.1379	1.0000	1.1339	1.0041
Western region	Chongqing	1.1339	1.0298	1.1365	0.9981
Western region	Sichuan	1.1096	0.9791	1.1231	0.9879
Western region	Guizhou	1.1161	0.9898	1.1191	0.9885
Western region	Yunnan	1.0398	0.9171	1.1329	0.9885
Western region	Shaanxi	1.0701	0.9589	1.1188	0.9749
Western region	Gansu	1.0661	1.0131	1.1231	0.9486
Western region	Qinghai	0.9968	0.9099	1.1221	0.9729
Western region	Ningxia	1.1010	0.9431	1.1206	0.9695
Western region	Xinjiang	1.0328	0.9291	1.1189	0.9851
Western region average value		1.0790	0.9750	1.1244	0.9790
Whole nation average value		1.0897	1.0005	1.1162	0.9811

From the decomposition of *GTFP,* technological progress plays a crucial role in enhancing *GTFP*, but the widening technological gap restrains the overall green development to some extent. From 2007 to 2021, the average value of *GTFP* of the manufacturing sector in eastern, central, and western regions was all higher than 1.000, indicating that the *GTFP* has increased in all regions, among which the eastern region had the largest growth with an average value of 1.1067, followed by the central region with an average value of 1.0836, and the last is 1.0790 in the western region. Beijing's *GTFP* grew the fastest with an average of 1.1602, in which technological progress played a major role. Among the 30 provinces, Heilongjiang and Qinghai have the negative growth

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN1785 0037 (Online)
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rate of *GTFP*, among which Heilongjiang has the lowest *GTFP* of 0.9888. The widening of the technical gap and the decrease in technical efficiency are the important reasons for the decrease in *GTFP*. Based on the decomposition item of *GTFP*, the improvement of technical efficiency facilitated the growth of *GTFP* in 15 provinces, among which the promotion impact on Anhui is the strongest, and the decrease of technical efficiency inhibited the growth of *GTFP* in 12 provinces, among which the inhibition impact on Qinghai is the strongest. Technological progress has contributed to *GTFP* growth in all provinces, with the strongest impact on Hubei. The narrowing of the technology gap only promoted the growth of *GTFP* in Guangxi, while the widening of the technology gap hindered the growth of *GTFP* in 18 provinces, among which Shanxi and Jilin had the strongest inhibition effect.

Spatial Dubin model analysis

According to *equation (7)*, the following non-spatial panel model is established:

LM and joint significance test of fixed effect for the "non-spatial panel model" are carried out to select the fixed effect model. The *P*-values of both the joint significance test of spatial fixed effect and joint significance test of temporal fixed effect are 0, and the "spatial-time dual fixed model" has the largest logL value, which indicates that the "spatial-time dual fixed effect model" should be selected (*Table 4*). Then the SDM model is established as follows:

$$GTFP=\alpha+\beta_0 DII+\beta_1 HUCA+\beta_2 IS+\beta_3 ENRE+\beta_4 FDI+\beta_5 ES+\boldsymbol{\mu}_i+\boldsymbol{\lambda}_t+\boldsymbol{\varepsilon}_{it} \quad \text{(Eq.11)}$$

Table 4. *Test results of the non-spatial panel model*

Variables	Mixed regression model	Spatial fixed effect model	Time-fixed effect model	Spatiotemporal double fixed model
log L	2248.8	2316.7	2305.8	2354.8
LM-Lag	156.5429***	109.1011***	0.0387	10.6982***
Robust LM-Lag	44.9502***	103.5071***	0.2293	7.5172***
LM-Error	131.7456***	67.4887***	0.1072	13.0536***
Robust LM-Error	20.1519***	61.8951***	0.2963	7.8732***
Joint significance test of spatial fixed effect	LR statistic=100.3778		P value =0.000 0	
Joint significance test of time-fixed effect	LR statistic=78.5979		P value =0.000 0	

Note: *, **, *** indicate passing the significance test at the 0.1, 0.05, and 0.01 levels, respectively. *LM-lag* and *LM*-error represent *LM* statistics to test the effect of spatial *Lag* autocorrelation and spatial error autocorrelation, respectively

Wald statistics and *LR* statistics are used to ascertain whether the *SDM* can be simplified into the SEM or SAR model. *Table 5* shows that *Wald* and *LR* statistics of *SDM* simplified to the *SAR* model both pass the 1% significance test, showing that *SDM* will not be simplified to the SAR model; *Wald* and *LR* statistics of *SDM* simplified to SEM both passed the 1% significance test, showing that *SDM* will not be simplified to *SEM*. Therefore, the *SDM* of "double fixed effect" in time and space should be selected for parameter analysis (*Table 5*).

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2304_81318148

Table 5. *Estimation results of the spatiotemporal dual fixed effect model*

Variables	Direct effect	Indirect effect	Total effect
ln*DII*	0.0014*** (4.4821)	0.0382*** (4.7822)	0.0385*** (4.7739)
ln*HUCA*	0.0051*** (2.9081)	0.1572*** (3.0952)	0.1619*** (3.0904)
ln*IS*	0.0023*** (3.2547)	0.0268*** (3.4269)	0.0279*** (3.6841)
lnENRE	0.0003** (2.1201)	0.0098 (1.4569)	0.0100 (1.4504)
ln*FDI*	-0.0001 (-0.5781)	-0.0067 (-1.5049)	-0.0068 (-1.4771)
ln*ES*	-0.0043*** (-4.8412)	0.1203*** (-4.9169)	-0.1245*** (-4.9157)
δ	0.4809*** (5.0834)		
Wald test (SAR)	20.3954***	*Wald test (SEM)*	19.5198***
LR test (SAR)	19.4394***	*LR test (SEM)*	18.7942***

Note: *, **, *** indicate passing the significance test at the 0.1, 0.05, and 0.01 levels, respectively. *LM-lag* and *LM*-error represent *LM* statistics to test the effect of spatial *Lag* autocorrelation and spatial error autocorrelation, respectively

The results in *Table 5* show that the green development in a region is not only influenced by the local digital infrastructure investment etc. factors but also influenced by the surrounding regions. The δ value of the spatial lag effect coefficient is 0.4810, and it passes the 1% significance test, indicating that the green development exhibits a significant *SSE*. The green development in one region can also effectively drive the green development in surrounding regions. This is mainly because the spatial proximity of the geographical location is conducive to the trade of goods, personnel, and technical exchanges in the adjacent regions. According to the industry correlation theory, this will significantly enhance green development in adjacent regions. The proximity of geographical location is conducive to the growth in the adjacent regions to form the downstream and upstream industrial chain and circular economy, to form the synergistic and circular impact of the growth of the regional manufacturing sector.

Under different effects, *DII* exerts a significant promoting influence on green development, which indicates that *DII* not only fosters local green development but also drives green development in the surrounding regions through *SSE*. First of all, the expansion of information resources scale and the enhancement of information processing capacity significantly accelerate the pace of innovation and upgrading, improve information efficiency, facilitate technological progress, and thus promote green development. Secondly, the advancement of digital technology will compel manufacturing companies to upgrade their outdated production equipment and adopt cleaner production technologies, thereby achieving the dual objectives of increasing profits and reducing carbon emissions. Finally, with the proliferation and application of digital technology, various regions will accelerate the profound integration of digitalization and the manufacturing sector, facilitate the transformation of manufacturing production modes to digital manufacturing, and propel the growth of the manufacturing sector towards being digital, green, and service-oriented.

Based on control variables, *HC* exerts a significant promoting impact on green development across all regions. The key to the green development of the manufacturing

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2304_81318148

sector hinges on the innovation of cleaner production technology, which is driven by talent. *HC* possesses strong mobility, and in the process of fostering local green development, it can also exert a spillover effect on the adjacent regions through flow and exchange. The *IS* plays a pivotal role in promoting green development across all regions. This is primarily attributed to the fact that an increased proportion of high-tech industries within the manufacturing sector can effectively decrease pollutant emissions and energy consumption, notably enhance the labor productivity of companies and technological level, and augment the technological added value of products, thereby exerting a significant promotional impact on the green development.

ER clearly promotes green development in the local region, yet it does not exert a significant influence on green development in the adjacent regions. The primary reasons for this are twofold. Firstly, as the government intensifies environmental regulations on manufacturing companies, these companies must upgrade their equipment, processes, and technologies, which facilitates green development. Secondly, as the stringency of environmental regulations in the region increases, polluting industries may relocate to adjacent regions, potentially hindering green development in those regions. Consequently, the impact of environmental regulations on the green development of manufacturing sectors in adjacent regions is not pronounced.

The impact of *FDI* on the green development of the manufacturing sector across all regions is not pronounced. This may be attributed to the following reasons: while *FDI* stimulates the growth of the manufacturing sector, it also leads to significant CO_2 emissions, which hinder green development. Conversely, *FDI* also introduces more environmentally friendly production technologies, fosters technological upgrades in manufacturing companies, and reduces CO_2 emissions. The technological benefits of *FDI* promote green development. Therefore, the overall effect of *FDI* on the green growth of the manufacturing sector is not significant, as these two opposing factors offset each other.

Under different effects, ECS exhibits a notable negative effect on the green development of the manufacturing sector. This is mainly because the coal-dominated *ECS* is not only detrimental to economic growth but also significantly increases pollutant emissions and energy consumption, which ultimately hinders green development.

$$\begin{gathered} GTFP_{it} = \delta\sum_{j=1}^{30} w_{ij}GTFP_{jt} + \alpha + \beta_0 DII + \beta_1 HUCA + \beta_2 IS + \beta_3 ENRE + \beta_4 FDI + \beta_5 ES \\ \gamma_0\sum_{j=1}^{30} w_{ij}DII_{jt} + \gamma_1\sum_{j=1}^{30} w_{ij}HUCA_{jt} + \gamma_2\sum_{j=1}^{30} w_{ij}IS_{jt} + \gamma_3\sum_{j=1}^{30} w_{ij}ENRE_{jt} + \gamma_4\sum_{j=1}^{30} w_{ij}FDI_{jt} \\ \gamma_5\sum_{j=1}^{30} w_{ij}ES_{jt} + \mu_i + \lambda_t + \varepsilon_{it} \end{gathered} \tag{Eq.12}$$

Analysis of spatial spillover effect (SSE) of digital infrastructure investment (DII)

To further reveal the spatial attributes of digitalization, Cheng et al. (2018) referred to test whether the *SSE* of digitalization on the green growth of the manufacturing sector has regional boundaries by setting different spatial weight matrices. In this research, the spatial weight matrix $W_{ij,d}$ with distance bandwidth is set as follows:

$$W_{\mathrm{ij}} = \begin{cases} \dfrac{1}{d_{ij}}, d_{ij} \ge d \\ 0, d_{ij} < d \end{cases} \tag{Eq.13}$$

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2304_81318148

where d_{ij} indicates the straight-line distance between two different provinces. This paper sets the initial distance as 50Km, and the distance threshold as 50Km, that is, the set space weight matrix is substituted into SDM for regression every 50Km. The resulting *SSE* coefficient is shown in *Table 6*.

The distance of *SSE* can be segmented into four sections as outlined in *Table 6*. The first interval spans from 50 Km to 200 Km, where the *SSE* gradually increases. This is primarily due to the short distance facilitating communication and collaboration between manufacturing companies. Adjacent regions can adopt clean production processes, and approach the production frontier through digitization, thereby enhancing *SSE*. The second section ranges from 200 Km to 800 Km, where the spillover effect exhibits a decreasing trend, indicating that manufacturing companies can use *DII* to promote their green development. The third section is between 800 Km and 1850 Km, the coefficient of *SSE* in this section changes slightly, indicating that the region in this section is less affected by the *SSE* of *DII* in the central region. The third section is the transition stage from positive influence to insignificant influence. The fourth section is the region beyond 1850 km. The *SSE* coefficient for this region does not pass the significance level test, indicating that there are geographical boundaries of the *SSE* of *DII*, beyond which the green development of the manufacturing sector cannot be promoted.

Analysis of action mechanism

To further analyze the mechanism of *DII* facilitating the green development of the manufacturing sector, this research kept the independent variables unchanged and adjusted the dependent variables into the technical efficiency change index (*TECI*), technological progress change index (*TPCI*), and technological gap change index (*TGCI*), and then adopt SDM for regression analysis (*Table 7*).

Technical efficiency, technological progress, and technological gap have significant *SSE*, which is mainly due to the rapidly updating of production equipment and technology in the manufacturing sector and the ability to flow between regions (*Table 7*). In addition, the coefficient of *SSE* of technological progress is greater than the coefficient of technological efficiency and technological gap, which indicates that the speed of technological replacement is greater than the speed of equipment upgrading. Technological progress is the main reason to facilitate the green development of the manufacturing sector.

Through the aforementioned analysis, it is evident that the investment in digital infrastructure significantly contributes to fostering technological progress and enhancing technological efficiency, while notably hindering the reduction of the technological gap, which indicates that green development is primarily propelled by advancing technological progress and improving technological efficiency. *DII* plays a more prominent role in promoting technological progress but inhibits green development by widening the technological gap. Although *DII* can stimulate green growth in both local and adjacent regions, the gap in manufacturing technology between regions induced by *DII* hinders the green development of the manufacturing sector to some extent.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2304_81318148

Table 6. *The SSE of DII changes with geographical distance*

Threshold value (KM)	***W--IT***		**Threshold value (KM)**	***W--IT***		**Threshold value (KM)**	***W--IT***		**Threshold value (KM)**	***W--IT***	
	Coefficient	**T-value**		**Coefficient**	**T-value**		**Coefficient**	**T-value**		**Coefficient**	**T-value**
50	0.0391^{***}	4.5121	550	0.0389^{***}	4.6559	1050	0.0201^{**}	2.5119	1550	0.0271^{***}	3.5648
100	0.0392^{***}	4.6814	600	0.0371^{***}	4.2857	1100	0.0212^{***}	2.6539	1600	0.0268^{***}	3.5645
150	0.0491^{***}	5.8291	650	0.0331^{***}	3.8319	1150	0.0231^{***}	2.9458	1650	0.0342^{***}	4.7950
200	0.0511^{***}	5.8269	700	0.0282^{***}	3.0921	1200	0.0181^{**}	2.2461	1700	0.0241^{***}	3.3895
250	0.0468^{***}	5.8929	750	0.0251^{***}	2.9251	1250	0.0214^{***}	2.7321	1750	0.0229^{***}	3.3908
300	0.0450^{***}	4.8718	800	0.0228^{**}	2.5726	1300	0.0203^{**}	2.5849	1800	0.0262^{***}	3.8579
350	0.0431^{***}	5.0141	850	0.0251^{***}	2.8639	1350	0.0221^{***}	2.9031	1850	0.0153^{**}	2.4609
400	0.0431^{***}	5.2531	900	0.0254^{***}	3.0629	1400	0.0204^{***}	2.8554	1900	-0.0005	-0.0718
450	0.0445^{***}	5.3607	950	0.0247^{***}	2.9939	1450	0.0275^{***}	3.4989	1950	-0.0005	-0.0801
500	0.0452^{***}	5.3836	1000	0.0271^{***}	3.4739	1500	0.0261^{***}	3.3582	2000	0.0003	0.0448

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2304_81318148

Table 7. *Estimated results of action mechanism*

Variables	TECI			TPCI			TGCI		
	Direct effect	Indirect effect	Total effect	Direct effect	Indirect effect	Total effect	Direct effect	Indirect effect	Total effect
ln*DII*	0.000 8*** (3.3960)	0.0320** (2.0665)	0.0316*** (2.7882)	0.0036*** (5.7341)	0.0418*** (4.2841)	0.0459*** (4.9040)	-0.0018** (-2.0740)	-0.0138 (-0.5713)	-0.0161 (-0.8501)
ln*HUCA*	0.0058*** (5.1359)	0.1751*** (3.9779)	0.1798*** (3.4645)	0.0039*** (4.5801)	0.1501*** (3.2371)	0.1540*** (3.7656)	0.0022*** (3.7650)	0.1240*** (2.9321)	0.1261*** (3.1851)
ln*IS*	0.0015*** (2.6462)	0.0261*** (3.7842)	0.0268*** (3.2098)	0.0027*** (3.6381)	0.0302*** (4.3602)	0.0331*** (3.4971)	0.0029 (1.2503)	0.0231*** (3.3551)	0.0261*** (2.8681)
ln*ENRE*	0.0006*** (2.8261)	0.0115 (1.1031)	0.0119 (1.3559)	0.0002** (2.1563)	0.0091 (0.8471)	0.0089 (1.0631)	0.0001 (0.8251)	0.0067 (0.5491)	0.0071 (0.7698)
ln*FDI*	0.002 (-0.7730)	-0.0063 (-0.9421)	-0.0039 (-1.1389)	-0.0015 (-0.5463)	-0.0046* (-1.8061)	-0.0059* (-1.8361)	-0.0008 (-0.6897)	-0.0081 (-1.4341)	-0.0088 (-1.4049)
ln*ES*	-0.0059*** (-6.8458)	-0.1331*** (-5.6492)	-0.1389*** (-5.1489)	-0.0049*** (-5.3442)	-0.1159*** (-4.7269)	-0.1209*** (-4.5039)	-0.0031*** (-4.2540)	-0.1218*** (-5.0391)	-0.1251*** (-4.8362)
δ	0.4569*** (5.2741)			0.5629*** (5.6949)			0.3748*** (4.5521)		
Wald test (SEM)	21.2851***	*Wald test (SEM)*	20.0441***	23.4157***	*Wald test (SEM)*	22.4279***	18.6431***	*Wald test (SEM)*	17.6891***
LR test (SEM)	20.2369***	*LR test (SEM)*	19.8651***	22.3281***	*LR test (SEM)*	21.5359***	17.5569***	*LR test (SEM)*	16.7139***

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2304_81318148

Discussion

The study explores the spatial spillover effect of digital infrastructure investment (DII) on the green development of China's manufacturing sector. The findings reveal that DII not only promotes local green development but also significantly enhances green development in neighboring regions through spatial spillover effects, with notable geographical boundaries.

As a key driver of green development, technological progress is accelerated by DII, which fosters innovation, upgrades production processes, improves resource utilization efficiency, and promotes cleaner production technologies. However, DII may widen the technology gap between regions, thereby hindering overall green development to some extent. The spatial spillover effect of DII exhibits a clear pattern, it increases within 50–200 km, decreases between 200–800 km, remains stable from 800–1,850 km, and becomes insignificant beyond 1,850 km. This indicates that geographical proximity facilitates knowledge and technology diffusion, while greater distances weaken such effects due to information asymmetry.

Control variables also play significant roles. Human capital and industrial structure upgrades have a positive impact on green development, whereas an energy consumption structure dominated by coal exerts a negative effect. Environmental regulations promote local green development but may lead to pollution transfer to adjacent regions, rendering their spillover effects ambiguous. Foreign direct investment shows no significant overall impact, as the conflicting effects of technology transfer and increased emissions neutralize each other.

In summary, DII is a powerful driver of green development in China's manufacturing sector. However, policymakers must address the technology gap and leverage spatial spillovers effectively to achieve sustainable growth.

Conclusions and policy implications

The main conclusions are as follows. First, *DII* not only fosters green growth within the local manufacturing sector, but also significantly enhances the green development of the adjacent ones through the *SSE*, and its *SSE* exhibits notable geographical boundary characteristics. Secondly, *DII* can stimulate green development by advancing technological progress to enhance technological efficiency, while also widening the technological gap and hindering the green development of the manufacturing sector.

Based on the research conclusions, the following policy implications are obtained. First, *DII* is used to promote green development in the manufacturing sector. *DII* has significantly contributed to green development. (1) Using digital infrastructure to improve the automation and digitization level of production processes and energy usage, thereby effectively improving resource utilization efficiency. (2) Using digital infrastructure to facilitate green transformation for manufacturing companies, encouraging them to adopt automation and digital technology to save energy and reduce emissions. (3) Accelerating the integrated development and utilization of digital and environmentally friendly technologies, innovating energy management through the application of digital technologies, and enhancing the utilization of digital technologies in areas such as resource recycling and industrial waste treatment.

Second, use *DII* to promote the technological progress and efficiency enhancement of the manufacturing sector. (1) The government should accelerate the development of advanced and high-end manufacturing, fostering and reinforcing high-tech industries and

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2304_81318148

emerging industries, while utilizing *DII* to facilitate the upgrading of manufacturing structure. (2) Using *DII* to enhance the technological innovation capabilities of the manufacturing sector, encouraging companies to accelerate the upgrading of technical equipment and process optimization. (3) Employing digital technology for *HC* management, financial management, and logistics management, thereby improving corporate management and innovation capabilities.

Third, strive to narrow the technological gap in the manufacturing sector. The technology gap hinders the green development effect of intelligent manufacturing. Consequently, the government should formulate targeted policies for the western and central regions, fostering a more conducive external development environment for attracting talent, funds, and technology to these areas. Simultaneously, the government should enhance scientific and technological collaboration and technology transfer between the central and eastern regions. The government must dismantle market segmentation and facilitate the free flow and efficient allocation of factors such as talent, technology, and capital across regions.

Acknowledgements. Key Project of the Hunan Provincial Social Science Foundation: Research on the Construction of Cross-Domain Governance Capacity for the Ecological Environment in the Wuling Mountain Ethnic Area (Project No. 24ZDB023).

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