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Analysis of the impact of digital financial development on green total factor productivity and its spatial spillover effects

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Abstract. This paper, based on provincial panel data from China, employs spatial econometric models and Data Envelopment Analysis (DEA) methods to systematically investigate the impact of digital financial development on Green Total Factor Productivity (GTFP) and its spatial correlation characteristics. The study finds that digital finance not only significantly enhances local green production efficiency but also generates positive spatial spillover effects on neighboring regions through technology diffusion and factor mobility. Heterogeneity analysis reveals distinct regional differences: the eastern region, leveraging its sound digital infrastructure and market-oriented mechanisms, forms a core diffusion effect; the western region is limited by its factor endowments and policy capacity, resulting in relatively constrained spillover effects; the central and northeastern regions, due to path dependence in traditional industries and factor siphoning, face differentiated transformation challenges. Finally, based on a coordinated governance logic of "core area radiation - growth pole cultivation - peripheral area compensation," the paper proposes constructing a differentiated policy framework. It emphasizes the integrated design of digital technology sharing, institutional innovation, and ecological compensation mechanisms to address regional development imbalances and to provide theoretical support and practical pathways for promoting green transition and spatially balanced development.

Keywords: GTFP, digital finance, DEA, SDM

1. Introduction

Against the dual backdrop of China's 14th Five-Year Plan, which explicitly calls for "accelerating digital development and building new advantages in the digital economy," and the deepening implementation of the "dual carbon" goals (carbon peaking and carbon neutrality), digital finance has emerged as a critical bridge linking supply-side financial reform with the digital transformation of the real economy. It has thus been entrusted with the strategic task of addressing regional development imbalances and driving the leap in green total factor productivity (GTFP). The State Council's 14th Five-Year Plan for Digital Economy Development (2022) emphasizes the need to "build a data factor market system and improve the digital financial infrastructure network." This policy rationale aligns closely with the "effective market and proactive government" synergy advocated by New Structural Economics (Lin Yifu) [1] —that is, to use institutional innovation to guide digital finance in optimizing resource allocation, correcting the spatial mismatch in traditional finance, and unlocking the differentiated potential of regional productivity growth.

At the same time, the full-scale launch of the "Eastern Data, Western Computing" initiative marks a systemic shift in the spatial configuration of digital infrastructure—from simple geographic dispersion to a coordinated restructuring of computing power, data, and algorithms. This national strategy resonates with the theory of growth poles (Perroux): the eastern region, leveraging its first-mover advantage in digital technology, has become an "innovation pole" that spreads technological dividends to the central and western regions through interconnected payment and clearing networks and digital technology spillovers. Meanwhile, the central and western regions, capitalizing on their energy and land resource endowments, have become hosts for large-scale data center clusters. This not only reduces the operational costs of digital finance but also compels local industries toward green transformation, thereby fostering a virtuous cycle of "environmental regulation – technological progress – productivity improvement."

1.1. Literature review

1.1.1. Research on digital finance

On April 1, 2020, during an inspection tour in Zhejiang Province, President Xi Jinping emphasized the importance of seizing opportunities brought by the digitalization of industries and the growth of the digital economy. He called for the acceleration of new infrastructure construction such as 5G networks and data centers, as well as the strategic deployment of emerging and future industries like digital economy, life sciences, and new materials. He also stressed the need to vigorously promote scientific and technological innovation to foster new growth drivers and form new momentum for development. As a research hotspot in recent years, digital finance has already attracted considerable academic attention. Guo Feng, Wang Jingyi, et al. [2] constructed a development index for digital inclusive finance in China and examined its spatial distribution characteristics. They found that since 2011, digital inclusive finance has made remarkable progress, with strong regional convergence. The development gap between the central-western and eastern regions has been gradually narrowing. Mu WW and Liu KF [3] investigated the impact of digital finance on corporate ESG performance. Their study revealed that digital finance improves ESG outcomes by easing firms' financial constraints, and this positive effect is especially significant for small and medium-sized enterprises. Similarly, Zhao Tao, Zhang Zhi, and Liang Shangkun [4] found that digital finance enhances entrepreneurial activity, thereby promoting high-quality economic development. They identified public entrepreneurship as a key mechanism through which the digital economy empowers high-quality growth. Xu Weixiang, Zhou Jianping, and Liu Chengjun [5] demonstrated that the development of the digital economy has a significant positive spatial spillover effect on carbon emission reduction, with notable differences across eastern, central, and western China. FENG SL, ZHANG R, and LI GX [6] and MA KL [7] confirmed that digital finance significantly promotes green technological innovation. Furthermore, RAZZAQ A and YANG XD [8], in their evaluation of the impact of digital finance on green growth, concluded that digital financial development fosters green economic development. YANG JH, WU Y, and HUANG BH [9] examined the relationship between digital finance and financial literacy, finding that financial literacy facilitates the spread of digital finance, and in turn, digital finance deepens financial literacy. This mutual reinforcement is especially evident among vulnerable groups (e.g., low-income populations, the elderly), helping to bridge the digital divide and support inclusive, high-quality development. Finally, Wu Fei, Hu Huizhi, and Lin Huiyan [10] studied the relationship between corporate digital transformation and capital market performance. They found that digital transformation significantly enhances stock liquidity, contributing to the stability and soundness of business operations. In summary, prior research on digital finance has yielded substantial findings, which provide a strong foundation for the present study's analysis.

1.1.2. Research on Green Total Factor Productivity

Green Total Factor Productivity (GTFP) is a critical indicator for measuring high-quality development. In the context of the national "Lucid waters and lush mountains are invaluable assets" initiative and the strategic planning of the dual carbon goals (carbon peaking and neutrality), environmental protection has become an essential component of high-quality growth. Regarding GTFP measurement, Li Y. and Chen Y. [11] employed the SBM-ML method to evaluate green total factor productivity in Guangdong Province. Their results indicate a steadily rising trend in Guangdong's GTFP over recent years. Shao Shuai, Fan Meiting, and Yang Lili [12] used an advanced Data Envelopment Analysis (DEA) approach to assess and decompose carbon emission performance across 30 Chinese provinces from 1996 to 2018. Incorporating a Spatial Durbin Model (SDM), they systematically examined the direct and indirect effects of factors such as economic structural adjustment and green technological advancement on carbon emission performance and found significant positive spatial spillover effects. Guo B. S., Yu H., and Jin G.[13] investigated urban GTFP in China using the Luenberger Productivity Indicator and its decomposition. They found a clear upward trend in China's GTFP from 2000 to 2019, highlighting notable progress in the country's sustainable development efforts. Zhao X., Nakonieczny J., and Jabeen F. [14] explored the impact of green innovation on GTFP at the city level and concluded that green innovation significantly enhances GTFP. Wang Pengfei, Liu Haibo, and Chen Peng [15] examined the relationship between enterprise digitalization and total factor productivity, revealing an evident inverted U-shaped relationship between the two. This relationship becomes more pronounced under conditions of environmental uncertainty. Ren Shenggang, Zheng Jingjing, and Liu Donghua et al. [16] studied the effect of emissions trading schemes on enterprise GTFP and found that such mechanisms significantly improve the GTFP of listed companies, especially in regions with stricter environmental regulations, where the promotion effect is even more evident. In summary, existing research on green total factor productivity has yielded a wealth of results, particularly at the micro level. However, studies from a macro perspective remain insufficient—especially those that address interregional interactions, which are still relatively scarce.

1.1.3. Literature review summary

To date, research on digital finance and green total factor productivity (GTFP) has produced abundant findings. Digital finance—by reshaping capital allocation efficiency, alleviating information asymmetries, and empowering technological innovation—has become a new engine for total factor productivity (TFP) growth. However, there remain significant gaps in the existing literature.

First, most studies focus on the direct economic effects of digital finance, while the mechanisms of spatial spillover and regional heterogeneity in its influence on GTFP are insufficiently explored. Second, in the context of unbalanced regional development, there is a pressing need for both theoretical and empirical examination of whether digital finance can foster high-quality growth or, conversely, exacerbate factor siphoning and widen the "digital divide." Key questions remain: Can the technological diffusion effect of eastern “innovation poles” benefit the central and western regions? Can the western regions, in receiving computing infrastructure, ultimately promote local high-quality development? Addressing such issues requires a comprehensive analytical framework that integrates environmental constraints and spatial interactions, providing a scientific basis for the coordinated advancement of the national unified market and the dual carbon goals.

In response, this study uses panel data from 29 Chinese provinces spanning 2011 to 2022. It first applies a non-radial SBM-GML model to measure GTFP and constructs a dynamic database of production efficiency under environmental constraints. Compared with traditional DEA methods, the SBM-GML approach enhances the identification of real productivity improvement potential across provinces by optimizing slack variables and referencing a global technological frontier, thereby producing a more robust dependent variable for analysis.

Furthermore, this research integrates the non-radial SBM-GML efficiency measurement with the Spatial Durbin Model (SDM) to build a comprehensive “efficiency evaluation–spatial interaction–mechanism deconstruction” analytical framework. Multiple spatial models are employed to capture both the direct local effects and indirect spatial spillover effects of digital finance on GTFP. In addition, sub-sample regressions are conducted for four major economic regions (eastern, central, western, and northeastern China) to reveal the regionally differentiated patterns of digital finance’s spatial effects.

1.2. Theoretical hypotheses

Yang Yaowu and Zhang Ping [17], in their study on China’s high-quality development, pointed out that there is no inherent convergence between rapid economic growth and high-quality development. Wu Changqi and Zhang Kunxian [18] found that the impact of digital financial inclusion on firms’ high-quality development follows a nonlinear, inverted U-shaped relationship—that is, a moderate degree of digitalization promotes high-quality development, while excessive or insufficient digitalization may not yield the same benefits. In addition, Du Longzheng, Zhao Yunhui, and Tao Ketao et al. [19], in their study of the Porter Hypothesis, found that environmental regulation stimulates technological innovation and enhances firms’ total factor productivity. Digital finance can further reinforce this mechanism. For example, through innovations in green financial instruments such as carbon futures and green asset-backed securities (ABS), digital finance helps internalize environmental externalities and incentivizes enterprises to adopt cleaner technologies in order to reduce emissions. Moreover, the synergy between policy tools—such as the integration of digital finance with carbon markets (e.g., using carbon quotas as collateral for financing)—can accelerate the development of clean technologies, thereby improving firms’ green total factor productivity. Based on this rationale, the first hypothesis of this study is proposed:

H1: The development of digital finance enhances green total factor productivity.

Furthermore, Li Rengui [20], in his study on growth pole theory in regional economics, concluded that economic growth initially emerges in innovation-intensive “core areas” (growth poles) and subsequently spreads to surrounding regions through diffusion effects. Lin Lan [21], in summarizing theories of technological diffusion, noted that under the framework of New Economic Geography, information flows more efficiently over short distances than long ones. The geographic distribution of economic activity is shaped by economies of scale, transport costs, and factor mobility. Digital finance platforms (e.g., Alipay, WeChat Pay) transcend geographical boundaries, lower interprovincial transaction costs, and facilitate the flow of green technologies, equipment, and services across regions. For example, green technology firms in eastern provinces may provide technology licenses to companies in central and western provinces via digital supply chain finance. In addition, digital finance—leveraging cloud computing and big data—can support the development of cross-provincial environmental data-sharing platforms (e.g., carbon emission monitoring systems), thereby helping neighboring regions optimize resource allocation efficiency. Based on these considerations, the second hypothesis is proposed:

H2: The development of digital finance has a positive spatial spillover effect on green total factor productivity.

Given the uneven levels of digital finance development across different regions of China, the spillover effects of digital finance are also likely to differ by region. Guo Feng, Wang Jingyi et al. [2] found that digital inclusive finance in China exhibits significant overall convergence. As of 2018, regions with well-developed digital finance were primarily located east of the Hu Line, while those to the west still showed substantial room for development—though the gap was gradually narrowing. At the same time, China’s regions differ markedly in terms of industrial structure, degree of financialization, economic development level, and infrastructure quality. The relatively advanced infrastructure in the eastern region may facilitate stronger collaborative effects from digital finance across regions. Hence, the third hypothesis is proposed:

H3: The spatial spillover effect of digital finance on total factor productivity varies across different regions.

1.3. Innovations and contributions of the paper

From a theoretical perspective, this study incorporates undesirable outputs (e.g., pollutant emissions) into the SBM-GML measurement framework, thereby constructing a dynamic evaluation system for green total factor productivity (GTFP) under environmental constraints. This approach overcomes the limitations of traditional DEA models that often neglect ecological costs, offering a new paradigm for quantifying the sustainable effects of digital financial development. Moreover, by integrating multiple spatial econometric models (such as the Spatial Durbin Model, SDM) with Data Envelopment Analysis (SBM-GML), the paper builds a dual-dimensional research framework of "efficiency and space." This enables simultaneous capture of both the direct impact of digital finance on local green productivity and its cross-regional spillover effects, addressing the methodological shortcoming in existing literature where efficiency evaluation and spatial relationships are treated separately.

From a practical standpoint, this paper conducts a regionally disaggregated analysis to systematically reveal the heterogeneous effects of digital finance on GTFP in eastern, central, western, and northeastern China. This provides a solid empirical foundation for future policy design. The study also proposes a forward-looking design strategy of "core area radiation – growth pole cultivation – peripheral area compensation," moving beyond traditional "blood transfusion-style" regional compensation models. Instead, it advocates for a new mechanism characterized by "self-sustaining growth – coordination – sharing" empowered by digital technology. This offers a novel digital finance-based solution to the long-standing issue of regional development imbalances in China.

2. Research design

2.1. Data sources

This paper uses panel data from 29 Chinese provinces covering the period from 2011 to 2022, comprising a total of 12 years and 348 observations. The data sources include the CSMAR Database, China Statistical Yearbook, and China Environmental Statistical Yearbook. The variables used in the analysis are shown in Table 1 below:

Table 1. Variable descriptions

Abbreviation	Name	Description
GTFP	Green Total Factor Productivity	A core indicator of high-quality development across regions, measured using the SBM-GML model.
dig	Digital Financial Inclusion Index	Provincial-level digital finance index developed by Peking University.
fin	Degree of financialization	Following Han Feng & Yang Ligao [22], and Liu Yi, Xia Jiezhang, Li Yao [23], this variable reflects the degree of financialization. It is measured as the ratio of financial sector output to total output and used as a control variable to comprehensively assess digital finance's effect on GTFP.
foreign_invest	Foreign investment	Amount of foreign direct investment (FDI) in each province.
lnrgdp	GDP per capita	Natural logarithm of per capita GDP for each province.
gdp_grouth	GDP growth rate	GDP growth rate of each province.
Consumption	Consumption level	Consumption index of each province.
GBE	General Budget Expenditures	Total general fiscal expenditure of each province.
LOR	Labor input	Average annual employment (labor input) in each province.
GDP	Gross domestic product	Gross Domestic Product of each province.
SO2	Sulphur dioxide emissions	Total sulfur dioxide (SO_2) emissions in each province.

2.2. Model construction

In the context of the coordinated advancement of the dual carbon goals and the high-quality development strategy, the measurement of Green Total Factor Productivity (GTFP) has shifted from a single economic-efficiency dimension toward a multidimensional framework integrating economic, environmental, and social aspects. Traditional DEA models, due to their neglect of slack in undesirable outputs and directional bias, struggle to accurately assess true production efficiency under environmental regulations. To address this issue, this study constructs a dynamic efficiency analysis framework by integrating the Slacks-Based Measure (SBM) model—enhanced to account for slack variables—with the Global Malmquist-Luenberger (GML) index. Using panel data from 29 Chinese provincial-level administrative units from 2011 to 2022 (excluding Tibet and Qinghai), the model systematically analyzes the driving mechanisms of total factor productivity growth under environmental constraints.

Drawing on the dynamic calculation approach of Li Y. and Chen Y. [11], the year 2011 is used as the base period, and each province in each year is treated as an independent Decision-Making Unit (DMU). The model is constructed as follows: assume there are n DMUs, denoted as DMU_j（$j = 1, 2, \ldots, n$）. Each DMU has m inputs, denoted as x_i（$i = 1, 2, \ldots, m$）, q_1 desirable outputs y_r（$r = 1, 2, \ldots, q_1$）, and q_2 undesirable outputs b_t($t=1,2,3\ldots\ldots q_2$). The DMU under evaluation is denoted as DMU_0. The SBM model with undesirable outputs is expressed as Equation (1):

$$min\ \rho = \frac{1-\frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{i0}}}{1+\frac{1}{q_1+q_2}\left(\frac{\sum_{r=1}^{q_1}s_r^+}{y_{r0}}+\frac{\sum_{t=1}^{q_2}s_t^{b-}}{b_{t0}}\right)} \tag{1}$$

$$s.t. \quad x_{i0} = \sum_{j=1}^{n}\lambda_j x_{ij} + s_i^-, \forall i$$

$$y_{r0} = \sum_{j=1}^{n}\lambda_j y_{rj} - s_r^+, \forall r$$

$$b_{t0} = \sum_{j=1}^{n}\lambda_j b_{tj} + s_t^{b-}, \forall t$$

$$\sum_{j=1}^{n}\lambda_j = 1$$

$$\lambda_j \geq 0, s_i^- \geq 0, s_r^+ \geq 0, s_t^{b-} \geq 0$$

Equation (1) defines the calculation method for the SBM model with undesirable outputs. The constraints s.t. represent the input, desirable output, and undesirable output conditions, respectively. Here, s_i^- denotes input slacks, s_r^+ denotes output shortfalls, and s_t^{b-} denotes slacks in undesirable outputs. The model $\sum_{j=1}^{n}\lambda_j = 1$ assumes variable returns to scale. Efficiency is achieved only when ρ = 1 and all slack variables (s_i^- , s_r^+ , s_t^{b-}) equal zero.

The Global Malmquist-Luenberger (GML) index is a classic method for measuring dynamic changes in total factor productivity that includes undesirable outputs (e.g., carbon emissions, pollutants). Its core formula is shown in Equation (2):

$$GML_t^{t+1} = \frac{1+\underset{D\ 0}{\rightarrow^{G}}(x_t, y_t, b_t; g)}{1+\underset{D\ 0}{\rightarrow^{G}}(x_{t+1}, y_{t+1}, b_{t+1}; g)} \tag{2}$$

In Equation (2), GML_t^{t+1} represents the index of GTFP change from period t to t+1; $\underset{D\ 0}{\rightarrow^{G}}\left(.\right)$ denotes the directional distance function under the global production technology set; x_t , y_t , and b_t represent inputs, desirable outputs, and undesirable outputs in period t, respectively; g is the directional vector, which determines the optimal path of expanding desirable outputs or contracting undesirable outputs. The calculation steps are as follows:

First, use the SBM model to compute the efficiency score for the base year (2011) via static linear programming.

Second, leverage the transitivity property of the GML index (cumulative multiplicative form) to calculate each DMU's relative efficiency score for subsequent years compared to the base year. That is, the GML index does not yield absolute productivity levels per year, but rather the relative GTFP compared to 2011: $E_0\left(x_0^t, y_0^t\right) = E_0\left(x_0^1, y_0^1\right) \times GML_1^2 \times GML_2^3 \ldots\ldots \times GML_{t-1}^t$

Next, the Spatial Durbin Model (SDM), one of the core models in spatial econometrics, is employed. By incorporating both the spatial lag of the dependent variable and the spatial lag of the explanatory variables, the SDM can effectively capture spatial dependence, spillover effects, and local impacts. The SDM model is specified as follows:

$$Y = \alpha WY + \beta X + \theta WX + \varepsilon, \varepsilon \sim N(\sigma^2 I) \tag{3}$$

In Equation (3), Y denotes the dependent variable, W is the spatial weight matrix, X is the matrix of explanatory and control variables, ε is the error term, α denotes the spatial autoregressive coefficient of the dependent variable (i.e., the intensity of spatial spillovers), β represents the direct effect coefficients, and θ indicates the coefficients of the spatially lagged explanatory variables (i.e., spatial spillover effects). The analytical framework of this study involves first calculating the GTFP of each province from 2011 to 2022 using the SBM-GML model. Based on the regression results, the SDM is then used to evaluate the spatial spillover effect of digital finance on GTFP. Robustness checks and further analysis are subsequently conducted.

3. Total factor productivity measurement

Total factor productivity (TFP) is first measured using the Slack-Based Measure (SBM) model calculated via STATA, followed by calculating the Global Malmquist-Luenberger (GML) index using MATLAB software. Drawing on the variable selection approach proposed by Li Y and Chen Y [11], the conventional capital variable typically uses the total fixed asset investment as a standard. However, since the publication standards changed after 2018, tests on related variables showed a strong correlation between general public fiscal expenditure and total fixed asset investment. Moreover, Granger causality tests confirmed this relationship. Therefore, to ensure data consistency over time and considering that Green Total Factor Productivity (GTFP) is a comprehensive indicator measuring high-quality development—not only reflecting capital input—general public fiscal expenditure is used as a proxy for fixed asset investment in perpetual inventory method to estimate capital stock K (with a depreciation rate of 9.6%). The average annual employment in each province is used as labor input L, the provincial annual GDP (in trillions) as the desired output Y, and the annual sulfur dioxide emissions as the undesired output (undesirable Y). The SBM efficiency results for 2011 calculated by STATA are shown in Table 2:

Table 2. SBM calculation results

	Obs	mean	sd	min	max
TE	29	0.58617	0.2845	0.2123	1
S_GBE	29	5571535	5254353	5.45e-08	1.50e+07
S_LOR	29	1046.157	936.1728	3.27e-12	3391.072
S_GDP	29	0.00059	0.0022148	5.70e-20	0.01165
S_SO2	29	318778.7	283592.7	1.09e-08	1004025

Here, TE represents the SBM efficiency in 2011; S_GBE and S_LOR denote input redundancies; S_GDP denotes output shortfall of the desired output; S_SO2 indicates the slack of the undesired output. From the table, it is evident that significant differences in GTFP exist among provinces in 2011.

After obtaining the SBM results for the base year, the GML index is computed using MATLAB. Following the same approach, annual GTFP is calculated, with partial provincial results shown in Table 3. Detailed results are provided in Appendix A.

Table 3. Partial provincial GTFP calculation results

pro	2011	2012	2013	2014	2015	2016
Beijing	1	0.995753	0.998102	1.007652	0.996247	1.006827
Liaoning	0.579066	0.575865	0.571458	0.583199	0.598342	0.566694
Jiangsu	0.972517	0.975405	1.032759	0.996077	0.997126	1.028542
Guangdong	1	1.004822	0.998788	1.011227	0.982983	1.024581
Sichuan	0.398569	0.396797	0.396966	0.402096	0.401445	0.418741
Shaanxi	0.387551	0.391032	0.391599	0.396241	0.389494	0.403145

2017	2018	2019	2020	2021	2022
1.035396	1.094972	1.180713	1.226706	1.369446	1.369446
0.571745	0.586661	0.579924	0.577106	0.59025	0.592358
1.056863	1.082481	1.106624	1.153125	1.292778	1.37772
1.087732	1.07355	1.121982	1.161101	1.2738	1.431221
0.434251	0.435676	0.446216	0.446773	0.458694	0.471186
0.414239	0.42189	0.424109	0.425797	0.437265	0.437185

The results indicate that overall, GTFP has maintained a steady upward trend since 2011, demonstrating China's steady progress toward high-quality economic development. However, clear disparities exist among provinces, with marked regional differences. The growth magnitude is also influenced by geographic distribution, suggesting the presence of regional characteristics among provinces, which provides a basis for studying spatial spillover effects.

4. Spatial econometric analysis

4.1. Descriptive statistics

The descriptive statistics of the relevant variables are presented in Table 4. The table shows that significant differences exist among provinces in terms of GTFP and dig over the 12-year period, providing a foundational premise for the regression analysis and research in this paper.

Table 4. Descriptive statistics

Variable	Obs	Mean	Std. dev.	Min	Max
GTFP	348	0.6068	0.3043	0.0251	1.4312
dig	348	245.2034	107.7062	18.4700	460.6900
lnrgdp	348	10.9170	0.4562	9.7058	12.1564
fin	348	0.0702	0.0323	0.0196	0.1991
gdp_grouth	348	0.0903	0.0672	-0.2502	0.2988
Consumption	348	102.3075	1.1727	100.1000	106.3380
foreign_invest	348	2814.2070	5544.5060	30.9821	56704.0000

4.2. Correlation test

A correlation test was conducted on the explanatory variables, with the results shown in Table 5. The results indicate no strong correlations among the explanatory variables, although some variables exhibit moderate correlations. To ensure robustness of the results, a Variance Inflation Factor (VIF) test was performed, with results shown in Table 6. The VIF test confirms the absence of significant multicollinearity, thus supporting the feasibility of subsequent regression analysis.

Table 5. Correlation test

	dig	lnrgdp	fin	gdp_grouth	con~	for~
dig	1.0000					
lnrgdp	0.6666	1.0000				
fin	0.4837	0.6469	1.0000			
gdp_grouth	-0.3936	0.2012	-0.2081	1.0000		
con~	-0.5970	-0.2662	-0.2039	0.4346	1.0000	
for~	0.3877	0.4295	0.2643	-0.0612	-0.1226	1.0000

Table 6. VIF test results

Variable	VIF	1/VIF
dig	2.92	0.3423
lnrgdp	2.60	0.3842
fin	1.76	0.5672
gdp_grouth	1.75	0.5719
con~	1.29	0.7738
for~	1.27	0.7852
Mean vif	1.93	

4.3. Spatial correlation test

To determine the feasibility of conducting spatial effects analysis, a spatial correlation test was conducted. Moran's I global spatial autocorrelation coefficient was used for this purpose. The spatial weight matrices were constructed with reference to the economic-geographical nested matrix method developed by Guo Yuqing and Sun Xifang (2017). For each year, matrices were constructed according to that year's GDP data. The results of the global Moran's I indices for GTFP and dig over the 12 years are presented in Table 7.

Table 7. Global Moran's I index

Year	TFP(I)	p-value*	DIG(I)	p-value*
2011	0.239	0.000	0.211	0.001
2012	0.216	0.000	0.185	0.000
2013	0.155	0.006	0.177	0.002
2014	0.130	0.000	0.148	0.000
2015	0.118	0.007	0.115	0.007
2016	0.161	0.000	0.162	0.000
2017	0.149	0.006	0.162	0.002
2018	0.123	0.000	0.148	0.000
2019	0.113	0.000	0.147	0.000
2020	0.127	0.000	0.150	0.000
2021	0.136	0.000	0.166	0.000
2022	0.155	0.003	0.164	0.002

The results show that the p-values for all years are less than 0.01, and the corresponding Moran's I values are positive. Therefore, the null hypothesis is rejected, indicating significant positive spatial autocorrelation. To further validate these results, a local Moran's I test was conducted, with the mapping results shown in Figures 1 and 2. (ID reference can be found in Appendix A)

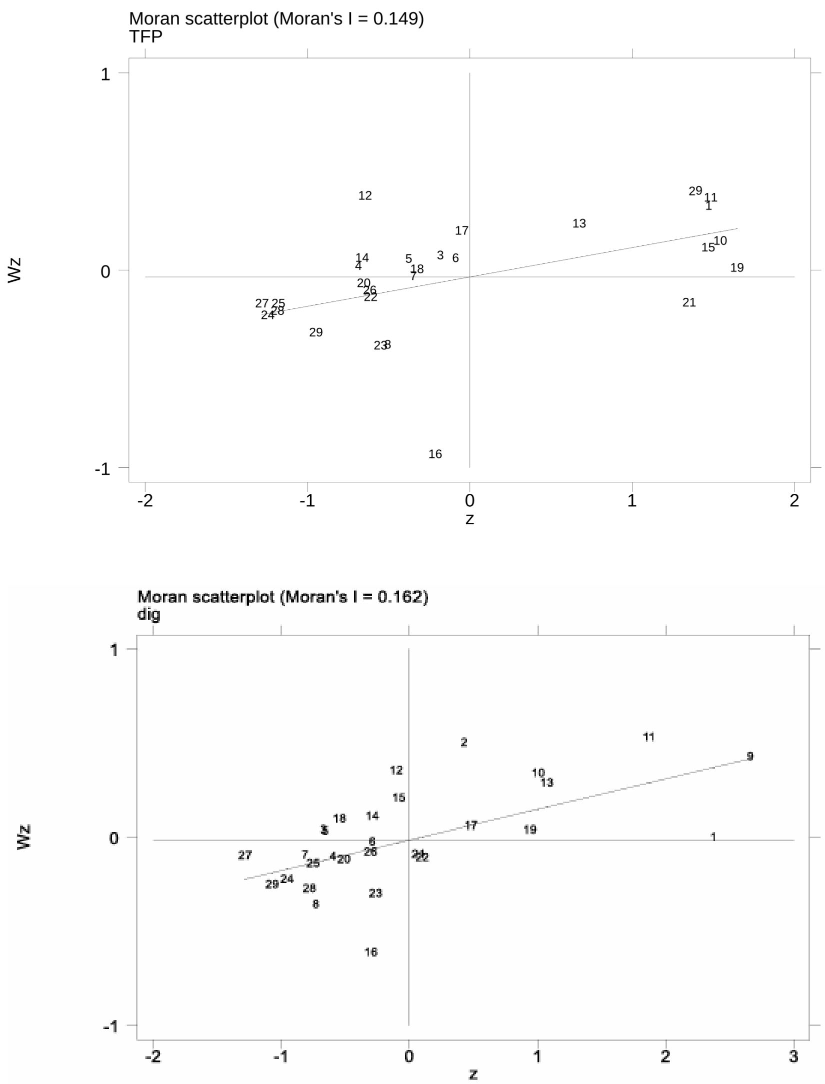

Figure 1. Local Moran's I map for 2017

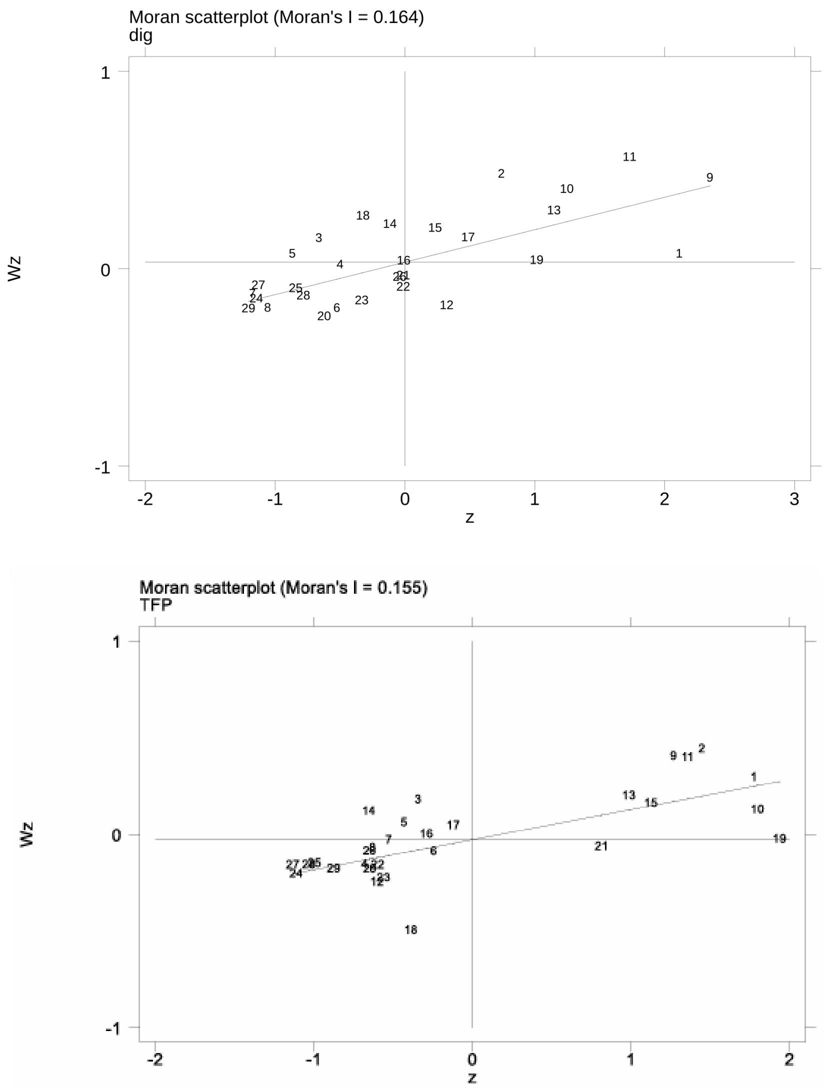

Figure 2. Local Moran’s I map for 2022

The results of the local Moran’s I maps show that most provinces exhibit positive spatial autocorrelation, further confirming the earlier test results and indicating that spatial effects analysis is feasible.

4.4. Model selection analysis

To determine the appropriate model, the Lagrange Multiplier (LM) tests were first conducted, with results presented in Table 8. The test results reveal that Moran’s I statistic is 173.128 (p = 0.000), strongly rejecting the null hypothesis of “no spatial autocorrelation,” indicating significant spatial dependence in the residuals. Both the LM and robust LM tests return p-values of 0.000, strongly rejecting their null hypotheses, suggesting significant spatial error autocorrelation. Meanwhile, the LM-lag test results show a significant p-value of 0.000 for the robust LM-lag but a non-significant p-value for the standard LM-lag test, indicating the possible presence of spatial lag effects. Given this, the Spatial Durbin Model (SDM), which accounts for both spatial lag and spatial error effects, is preliminarily considered the most appropriate choice.

Table 8. LM test results

Test	Statistic	P-value
Spatial error:		
Moran's I	173.128	0.000
Lagrange multiplier	14.405	0.000
Robust Lagrange multiplier	21.743	0.000
Spatial lag:		
Lagrange multiplier	0.103	0.748
Robust Lagrange multiplier	7.441	0.006

To further determine the optimal model, regressions with time-fixed effects, individual-fixed effects, and two-way fixed effects were conducted. Subsequent information criteria (IR tests) yielded test statistics of 889.92 ($p = 0.000$) comparing two-way fixed effects with time-fixed effects, and 106.88 ($p = 0.000$) comparing two-way fixed effects with individual-fixed effects, indicating that the two-way fixed effects model is optimal. For model selection among the Spatial Autoregressive Model (SAR), Spatial Error Model (SEM), and Spatial Durbin Model (SDM), all three were estimated under two-way fixed effects, and likelihood ratio (LR) tests were performed. The LR test statistics were 101.59 ($p = 0.000$) for SDM vs. SAR and 102.86 ($p = 0.000$) for SDM vs. SEM, suggesting that the SDM outperforms the SAR and SEM models. Finally, to verify whether the SDM degenerates into SAR or SEM models, Wald tests were conducted based on the SDM regression results. The Wald statistics were 84.09 ($p = 0.000$) for SDM vs. SAR and 99.28 ($p = 0.000$) for SDM vs. SEM, both strongly rejecting the null hypothesis. This indicates that the SDM does not degenerate into either the SAR or SEM model. In summary, the Spatial Durbin Model with two-way fixed effects will be employed for the analysis.

4.5. Regression results analysis

The regression results of the relevant variables using the Spatial Durbin Model (SDM) with two-way fixed effects are shown in Table 9. From the regression output, it can be observed that dig (digital development) has a significant positive impact on GTFP (Green Total Factor Productivity), both in terms of its direct and indirect effects. This indicates a clear positive spillover effect between neighboring provinces—whether viewed from economic or geographic perspectives. This finding aligns with the initial expectations: digital development promotes the GTFP of the province itself and also exerts positive externalities on surrounding provinces. Hypothesis 1 and Hypothesis 2 are thus validated. Furthermore, lnrgdp (the natural logarithm of real GDP) has a positive effect on the local province's GTFP but a negative effect on neighboring provinces, which could be attributed to a talent siphoning effect—provinces with higher living standards tend to attract more talent, depriving surrounding regions of human capital. In contrast, the GDP growth rate shows a suppressive effect on the province's GTFP, possibly due to the environmental degradation associated with rapid development. This underscores the necessity for China to pursue high-quality development. The regression coefficient ρ (rho) is significantly positive, indicating the presence of spatial autocorrelation in the dependent variable, GTFP. This is consistent with the Moran's I results discussed earlier, providing mutual validation. It suggests that provinces with higher GTFP levels may drive improvements in the GTFP of neighboring provinces, displaying the characteristics of growth pole effects.

Table 9. SDM regression results

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Main	Wx	Spatial	Variance	LR_Direct	LR_Indirect	LR_Total
dig	0.000820**	0.00261***			0.00122***	0.00350***	0.00471***
	(0.000350)	(0.000441)			(0.000341)	(0.000497)	(0.000581)
fin	0.762***	0.294			0.816***	0.619	1.435***
	(0.274)	(0.382)			(0.269)	(0.431)	(0.534)
foreign_invest	7.70e-07	7.61e-07			9.61e-07*	1.30e-06	2.27e-06*
	(4.76e-07)	(8.13e-07)			(5.01e-07)	(1.01e-06)	(1.34e-06)
lnrgdp	0.116***	-0.180***			0.0951***	-0.180***	-0.0850*
	(0.0265)	(0.0405)			(0.0258)	(0.0458)	(0.0513)
gdp_grouth	-0.0781*	0.0220			-0.0783*	-0.00473	-0.0830
	(0.0415)	(0.0651)			(0.0436)	(0.0792)	(0.105)
Consumption	0.0122**	0.0127**			0.0148***	0.0206**	0.0354***
	(0.00487)	(0.00632)			(0.00529)	(0.00891)	(0.0125)
rho			0.274***				
			(0.0492)				
sigma2_e				0.000986***			
				(7.60e-05)			
Observations	348	348	348	348	348	348	348
R-squared	0.126	0.126	0.126	0.126	0.126	0.126	0.126
Number of id	29	29	29	29	29	29	29

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

4.6. Robustness test

To verify the robustness of the results, the SAR (Spatial Autoregressive Model) and SEM (Spatial Error Model) were employed for regression analysis. The results of the SAR model are shown in Table 10. The regression results reveal that the rho coefficient remains significantly positive, consistent with previous findings, indicating the existence of positive spatial autocorrelation. The regression results of the SEM model are presented in Table 11. The lambda coefficient is significantly positive, indicating that unobserved factors in neighboring regions exert a significant positive influence on the dependent variable (i.e., GTFP) in the current region. This finding is in line with the results obtained from the previous SDM model analysis.

Table 10. SAR regression results

VARIABLES	(1) Main	(2) Spatial	(3) Variance	(4) LR_Direct	(5) LR_Indirect	(6) LR_Total
dig	0.00209***			0.00224***	0.00100***	0.00324***
	(0.000329)			(0.000350)	(0.000218)	(0.000506)
fin	0.386			0.397	0.178	0.575
	(0.271)			(0.282)	(0.134)	(0.413)
foreign_invest	4.58e-07			5.38e-07	2.46e-07	7.84e-07
	(4.87e-07)			(5.01e-07)	(2.40e-07)	(7.36e-07)
lnrgdp	0.0505**			0.0530*	0.0242*	0.0771*
	(0.0250)			(0.0270)	(0.0137)	(0.0401)
gdp_grouth	-0.0308			-0.0328	-0.0150	-0.0477
	(0.0441)			(0.0459)	(0.0217)	(0.0673)
Consumption	0.0109**			0.0119**	0.00537**	0.0173**
	(0.00511)			(0.00541)	(0.00271)	(0.00797)
rho		0.351***				
		(0.0475)				
sigma2_e			0.00116***			
			(9.05e-05)			
Observations	348	348	348	348	348	348
R-squared	0.125	0.125	0.125	0.125	0.125	0.125
Number of id	29	29	29	29	29	29

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 11. SEM regression results

VARIABLES	(1) Main	(2) Spatial	(3) Variance
dig	0.00175***		
	(0.000460)		
fin	0.357		
	(0.292)		
foreign_invest	2.35e-07		
	(4.83e-07)		
lnrgdp	0.0659**		
	(0.0295)		
gdp_grouth	-0.0286		
	(0.0450)		
Consumption	0.00649		
	(0.00510)		
lambda		0.330***	
		(0.0658)	
sigma2_e			0.00125***
			(9.93e-05)
Observations	348	348	348
R-squared	0.155	0.155	0.155
Number of id	29	29	29

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

To further verify the robustness and considering that the diffusion of digital finance depends more on information technology infrastructure rather than traditional transportation systems, this study, referring to the approach of XX, constructs an inverse squared economic distance matrix. Based on this revised spatial matrix, the SDM model was re-estimated using the same dataset. The regression results are shown in Table 12. The findings remain broadly consistent with previous results. The coefficient of Wx (spatial lag of dig) is significantly positive, further confirming that the development of digital finance has a clear and positive spatial spillover effect on total factor productivity. This provides strong evidence of the robustness of the findings.

Table 12. SDM regression results

VARIABLES	(1) Main	(2) Wx	(3) Spatial	(4) Variance	(5) LR_Direct	(6) LR_Indirect	(7) LR_Total
dig	0.00188***	0.00149***			0.00213***	0.00235***	0.00448***
	(0.000292)	(0.000396)			(0.000295)	(0.000435)	(0.000552)
fin	0.0216	1.353***			0.174	1.619***	1.792***
	(0.238)	(0.334)			(0.240)	(0.425)	(0.567)
foreign_invest	9.93e-07**	8.36e-07			1.17e-06**	1.28e-06	2.44e-06*
	(4.84e-07)	(8.37e-07)			(5.05e-07)	(1.00e-06)	(1.31e-06)
lnrgdp	0.0493***	-0.0596***			0.0590***	-0.0673***	-0.00823
	(0.0120)	(0.0153)			(0.0111)	(0.0127)	(0.0174)
gdp_grouth	-0.0343	-0.0627			-0.0436	-0.0804	-0.124
	(0.0415)	(0.0647)			(0.0426)	(0.0781)	(0.102)
Consumption	0.0148***	0.0112*			0.0166***	0.0179**	0.0345***
	(0.00498)	(0.00655)			(0.00510)	(0.00803)	(0.0110)
rho			0.243***				
			(0.0504)				
sigma2_e				0.00107***			
				(8.22e-05)			
Observations	348	348	348	348	348	348	348
R-squared	0.107	0.107	0.107	0.107	0.107	0.107	0.107
Number of id	29	29	29	29	29	29	29

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

5. Heterogeneity analysis

Given the significant differences in industrial structures and levels of digital development across various regions in China, the impact of digital finance on Green Total Factor Productivity (GTFP) is unlikely to be uniform across all provinces. Therefore, this study divides the 29 participating provinces into four groups—Eastern, Northeastern, Central, and Western—and conducts separate SDM regressions for each group. The corresponding indirect effect coefficients are summarized, and the integrated results are presented in Table 13. The results indicate that the impact of digital finance development on GTFP varies across regions, thereby supporting Hypothesis H3. Specifically, in the Eastern region, due to its well-developed infrastructure and advanced level of economic development, the positive spatial spillover effect of digital finance on GTFP is more pronounced. In the Western region, digital finance also shows a positive impact on GTFP, which may be attributed to the national Western Development Strategy. However, compared to the Eastern region, the Western region experiences a siphoning effect, as evidenced by the significantly negative coefficients of lnrgdp and fin. Economically developed provinces may attract more talent and resources, potentially exerting negative effects on neighboring provinces' GTFP, thereby offsetting part of the policy impact. The situation in the Northeastern and Central regions appears more severe. The Northeastern region has suffered significant population loss in recent years and, as a traditional heavy industrial base in China, faces challenges in achieving a high-quality transformation due to the high costs and long cycles involved. The diffusion of digital finance, influenced by factors such as population mobility and industrial structure, has failed to generate positive spillover effects; instead, a siphoning effect is observed. In the Central region, which serves as a transitional zone between the Eastern and Western regions, it lacks both the economic advantage of the East and the policy support received by the West. Fierce competition for resources and technology among provinces has resulted in an even more significant siphoning effect. This suggests that further policy guidance and support are needed to mitigate these disparities.

Table 13. Regional regression results

VARIABLES	Eastern Region	Central Region	Western Region	Northeastern Region
dig	0.00554***	-0.00146***	0.000466*	-0.00253*
	(0.00103)	(0.000437)	(0.000266)	(0.00138)
fin	1.297*	-0.192	-0.460***	1.192
	(0.672)	(0.378)	(0.160)	(1.185)
foreign_invest	-4.62e-06***	8.84e-06*	1.56e-06	5.53e-05***
	(8.90e-07)	(4.96e-06)	(1.45e-06)	(1.53e-05)
lnrgdp	0.0235	0.00599	-0.0596***	0.241**
	(0.0778)	(0.0366)	(0.0153)	(0.0944)
gdp_grouth	0.000889	-0.0232	-0.00328	-0.0737
	(0.132)	(0.0346)	(0.0318)	(0.140)
Consumption	0.0248**	-0.00314	0.000373	0.0194*
	(0.0117)	(0.00636)	(0.00247)	(0.0102)
rho	0.189**	-0.471***	0.275***	-0.214
	(0.0829)	(0.123)	(0.0850)	(0.178)
sigma2_e	0.00116***	1.75e-05***	3.99e-05***	1.72e-05***
	(0.000151)	(3.12e-06)	(5.21e-06)	(3.76e-06)
Observations	120	72	120	36
R-squared	0.196	0.059	0.140	0.046
Number of id	10	6	10	3

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

6. Conclusion and recommendations

By systematically constructing a Spatial Durbin Model (SDM), this study verifies the existence of a significant positive relationship between the development of digital finance and Green Total Factor Productivity (GTFP). The empirical results demonstrate that digital finance not only significantly enhances local green production efficiency (direct effect coefficient β=0.000820**, significant at the 5% level), but also exerts positive spillover effects on neighboring regions (indirect effect θ =0.00261***, significant at the 1% level). Moreover, the green empowerment effect of digital finance exhibits pronounced spatial heterogeneity. The impact of digital finance on green transformation is deeply influenced by the regional endowment structure. In the eastern region, the concentration of human capital and solid economic foundations enable a synergistic and multiplicative effect between digital finance and green technologies. The western region benefits from policy-driven subsidies, which provide a positive impetus for development. However, due to factors such as industrial structure, population mobility, and lower levels of economic development, the northeastern and central regions have not fully realized the potential positive spillovers of digital finance. In fact, these regions experience siphoning effects that suppress the green development of surrounding areas. Therefore, targeted policy guidance and support are necessary.

In response, this paper proposes a “Core Radiation – Growth Pole Cultivation – Peripheral Compensation” development strategy: First, in eastern core areas such as the Yangtze River Delta and the Guangdong–Hong Kong–Macao Greater Bay Area, efforts should focus on strengthening technological innovation capacity and institutional spillover mechanisms. This includes establishing joint innovation centers for digital finance and green technologies, promoting the diffusion of technologies like blockchain and artificial intelligence across industrial chains. In parallel, core-region computing power platforms should be opened for public access to build a shared cross-regional digital infrastructure network, thereby expanding the radius of technology spillovers. Second, in high-potential western regions such as the Chengdu–Chongqing Economic Circle and the Guanzhong Plain, efforts should focus on cultivating new growth poles by integrating digital finance development with ecological governance projects, guiding the targeted agglomeration of key production factors, and overcoming the “digital divide" in technological adoption and capability. Finally, for the old industrial bases in the northeast and transitional zones in central China, a comprehensive transformation compensation system should be established. This includes the creation of a digital transformation fund to provide direct subsidies to related industries, and the construction of a "Central China Green Finance Corridor". Through institutional innovation, these initiatives can offset siphoning effects and ensure regional coordination. Furthermore, a national unified digital talent certification system and data element circulation platform should be established to facilitate cross-regional government data sharing and flexible allocation of computing power resources. The Gross Ecosystem Product (GEP) should also be incorporated into fiscal transfer payment evaluations, ultimately forming a virtuous cycle of "core-driven innovation, distinctive growth pole development, and institutional compensation for peripheral regions."

7. Limitations and future outlook

This study constructs a spatial econometric model and an efficiency analysis framework to preliminarily reveal the mechanisms through which digital finance affects Green Total Factor Productivity (GTFP) and the spatial heterogeneity of these effects. However, several limitations remain that warrant further exploration. First, in terms of data granularity, this study relies on province-level panel data for empirical analysis. While such data captures broad regional development patterns, it falls short in identifying intra-urban cluster dynamics, such as gradients of technology diffusion and the effects of administrative boundaries. This limitation is particularly relevant in cross-provincial innovation corridors such as the Yangtze River Delta and the Guangdong–Hong Kong–Macao Greater Bay Area, where technology spillovers may transcend provincial administrative units. Future research should consider constructing a multi-level nested dataset (province–city–county) and adopt methodologies such as multi-scale geographically weighted regression to better reveal the spatial spillover effects of digital finance.

Second, in terms of thematic depth, this study focuses primarily on the direct relationship between digital finance and green productivity as well as its spatial effects, but does not yet systematically analyze the mediating mechanisms of technological innovation, factor reallocation, and institutional transformation. Future research could explore indirect effects of digital finance through mediating variables such as green patent output and carbon market liquidity, especially focusing on how these mechanisms differ across regions—a topic that merits in-depth investigation.

Third, the heterogeneity analysis in this paper has not yet been fully integrated with China's New Urbanization Strategy. Future research may consider focusing on the following areas: (1) In relation to the "East-to-West Computing Resource Transfer" (East-Data-West-Computing) project, examine the spatial alignment efficiency of computing infrastructure and its leverage effect on green technology diffusion. (2) From the perspective of land-sea coordination, establish a digital value chain co-construction mechanism between coastal core cities and inland node cities, in order to resolve the "green transformation isolation" problem in peripheral regions. These future directions will not only enrich the theoretical system of digital economic geography, but also provide policy recommendations and decision-making support for China's national regional coordination strategy.

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Appendix A

Appendix 1: SBM-GML estimation results

	2011	2012	2013	2014	2015	2016
Beijing	1	0.995753	0.998102	1.007652	0.996247	1.006827
Tianjin	1	0.987905	0.964339	0.953757	0.949896	0.963886
Hebei	0.552592	0.545529	0.545419	0.54516	0.528762	0.537248
Shanxi	0.395637	0.386809	0.383241	0.381489	0.371507	0.376053
Inner Mongolia	0.502589	0.503766	0.502972	0.506356	0.498665	0.503184
Liaoning	0.579066	0.575865	0.571458	0.583199	0.598342	0.566694
Jilin	0.486497	0.488379	0.489548	0.495068	0.488685	0.491479
Heilongjiang	0.441948	0.436191	0.461516	0.449879	0.434498	0.442741
Shanghai	1	0.999117	1.018442	0.991436	0.975546	0.987618
Jiangsu	0.972517	0.975405	1.032759	0.996077	0.997126	1.028542
Zhejiang	1	0.998181	0.992316	0.995548	0.975048	1.0036
Anhui	0.394663	0.386093	0.388614	0.390665	0.386815	0.399865
Fujian	0.846398	0.771085	0.760652	0.771928	0.759349	0.775896
Jiangxi	0.400806	0.391716	0.385606	0.386476	0.381334	0.395788
Shandong	1	0.992394	0.992439	1.004049	0.998277	1.013362
Henan	0.512212	0.505034	0.501689	0.508499	0.506868	0.522349
Hubei	0.562335	0.558838	0.553501	0.561138	0.549006	0.575382
Hunan	0.476614	0.474997	0.469519	0.478076	0.474171	0.486435
Guangdong	1	1.004822	0.998788	1.011227	0.982983	1.024581
Guangxi	0.406661	0.397633	0.401162	0.403186	0.395027	0.407831
Hainan	1	0.992536	0.858568	0.959763	0.83651	0.972329
Chongqing	0.37664	0.375905	0.386605	0.393711	0.392025	0.408826
Sichuan	0.398569	0.396797	0.396966	0.402096	0.401445	0.418741
Guizhou	0.212342	0.205125	0.209909	0.211891	0.214329	0.220231
Yunnan	0.245354	0.239165	0.23882	0.24187	0.242162	0.24525
Shaanxi	0.387551	0.391032	0.391599	0.396241	0.389494	0.403145
Gansu	0.236309	0.23099	0.231762	0.231262	0.212405	0.214775
Ningxia	0.290367	0.290367	0.248861	0.273932	0.267141	0.25618
Xinjiang	0.321487	0.317748	0.314222	0.32668	0.313586	0.316326
	2017	2018	2019	2020	2021	2022
Beijing	1.035396	1.094972	1.180713	1.226706	1.369446	1.369446
Tianjin	1.005269	1.242356	0.960753	1.013942	1.083327	1.242356
Hebei	0.543691	0.545088	0.538642	0.541092	0.553953	0.555195
Shanxi	0.393628	0.407689	0.403849	0.398588	0.422335	0.425276
Inner Mongolia	0.485975	0.494785	0.49261	0.493578	0.515059	0.520756
Liaoning	0.571745	0.586661	0.579924	0.577106	0.59025	0.592358
Jilin	0.494489	0.495443	0.459298	0.471491	0.489293	0.483488
Heilongjiang	0.447458	0.45816	0.427444	0.416713	0.440815	0.445104
Shanghai	1.008919	1.009591	1.049397	1.065	1.143967	1.173811
Jiangsu	1.056863	1.082481	1.106624	1.153125	1.292778	1.37772
Zhejiang	1.029585	1.032621	1.046117	1.095748	1.172846	1.208475
Anhui	0.405973	0.428428	0.439012	0.446057	0.456394	0.455579
Fujian	0.798325	0.825707	0.876329	0.92362	1.065728	1.065728
Jiangxi	0.400416	0.408729	0.418231	0.419048	0.432527	0.435625
Shandong	1.034868	1.052665	1.026637	1.0515	1.084312	1.119219
Henan	0.534367	0.535938	0.568696	0.558237	0.576204	0.575075

Hubei	0.58316	0.589756	0.603196	0.591471	0.638669	0.639971
Hunan	0.501127	0.503205	0.506477	0.511042	0.529101	0.537303
Guangdong	1.087732	1.07355	1.121982	1.161101	1.2738	1.431221
Guangxi	0.403397	0.4146	0.416043	0.415074	0.43314	0.437882
Hainan	1	0.967127	1	0.910057	0.927411	1
Chongqing	0.41593	0.41747	0.426187	0.434161	0.449317	0.457143
Sichuan	0.434251	0.435676	0.446216	0.446773	0.458694	0.471186
Guizhou	0.227452	0.230343	0.236951	0.249536	0.259974	0.259471
Yunnan	0.247048	0.25283	0.279212	0.288793	0.299942	0.30382
Shaanxi	0.414239	0.42189	0.424109	0.425797	0.437265	0.437185
Gansu	0.216797	0.216233	0.221369	0.225711	0.250514	0.251128
Ningxia	0.245098	0.241162	0.259752	0.253828	0.290367	0.290367
Xinjiang	0.315689	0.332191	0.339677	0.34213	0.361456	0.350473

Appendix 2: ID reference table

id	pro
1	Beijing
2	Tianjin
3	Hebei Province
4	Shanxi Province
5	Inner Mongolia Autonomous Region
6	Liaoning Province
7	Jilin Province
8	Heilongjiang Province
9	Shanghai
10	Jiangsu Province
11	Zhejiang Province
12	Anhui Province
13	Fujian Province
14	Jiangxi Province
15	Shandong Province
16	Henan Province
17	Hubei Province
18	Hunan Province
19	Guangdong Province
20	Guangxi Zhuang Autonomous Region
21	Hainan Province
22	Chongqing
23	Sichuan Province
24	Guizhou Province
25	Yunnan Province
26	Shaanxi Province
27	Gansu Province
28	Ningxia Hui Autonomous Region
29	Xinjiang Uygur Autonomous Region