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Unveiling the Mechanisms and Spatial Spillovers of Digital Finance in Enhancing Urban Green Efficiency

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Abstract: The rapid advancement of digital finance has emerged as a crucial driver of sustainable urban development, yet its impact on green total factor productivity (GTFP) remains underexplored. This study investigates the mechanisms through which digital finance influences GTFP and examines its spatial spillover effects within Chinese prefecture-level cities. Utilizing panel data from 278 cities spanning 2011 to 2021, the Digital Financial Inclusion Index and an urban GTFP measurement framework are employed to conduct a dynamic analysis. The findings reveal that digital finance facilitates GTFP growth primarily through three channels: fostering technological innovation, promoting industrial upgrading, and mitigating resource misallocation. Significant regional heterogeneity is observed, with the impact being more pronounced in central and western China compared to the eastern region. Moreover, cities with lower levels of financial development experience a stronger enhancement in GTFP through digital finance than their more financially developed counterparts. A temporal analysis further indicates that the green efficiency effect of digital finance has intensified over time. Employing a Spatial Error Model (SEM), robust evidence of significant spatial spillover effects is identified, demonstrating a clustering pattern in regional green efficiency improvements. These findings underscore the need for tailored policy interventions to optimize the role of digital finance in promoting sustainable urban development. Policy recommendations include enhancing financial accessibility in underdeveloped regions, strengthening technological diffusion, and fostering coordinated regional green development strategies.

Keywords: Prefecture-level cities; Robustness test; Green total factor productivity (GTFP); Digital financial inclusion index; Spatial Error Model (SEM); Sustainable urban development; Technological innovation; Industrial upgrading; Spatial spillover effects

1. Introduction

According to Rostow's Take-off Model, China's economic development has experienced a take-off stage of ultra-high-speed growth with an average annual growth rate of 10% from 1978 to 2010, after which China's GDP growth rate has slowed down and moved towards a high-quality maturity stage. The World Bank's latest study points out that China, India, and other developing countries face multiple obstacles, such as population and ecology, before becoming high-income countries, making it difficult to realize high-quality growth. In order to get out of the Middle-Income Trap, developing countries must balance the power of preservation and destruction, and head for sustainable development. China joined the Paris Agreement in 2016, and is jointly committed to combating climate change, assuming the responsibility of reducing emissions and promoting sustainable development. In 2020, the Chinese government also put forward the goal of carbon peaking by 2030 and carbon neutrality by 2060. The concept of sustainable development had already become a consensus in the international community.

Green economy is an important way to realize sustainable development, and the development of green economy cannot be separated from the strong support of the financial industry. According to the People's Bank of China, at the end of 2023, the green loans balance of local and foreign currency amounted to 30.08 trillion yuan, of which loans invested in projects with direct and indirect carbon emission reduction benefits amounted to 10.43 and 9.81 trillion yuan, respectively, accounting for a total of 67.3% of the green loans; 212,000 science and technology-oriented SMEs were supported by the loans, more than 54.2% of which were able to obtain loans, and the balance of loans for high-tech enterprises in both local and foreign currencies amounted to 13.64 trillion yuan. However, as China's green economy is still in the primary development stage, the integration of the financial industry with the green economy is still relatively low, triggering problems such as low service efficiency in green finance, insufficient innovation vitality, and difficulties in financing for small and medium-sized enterprises, thus failing to support the further development of the green economy. With the arrival of Industry 4.0, the financial industry has deeply embraced digital technology, which has injected new vitality and brought new opportunities for economic development. The traditional financial industry has utilized digital technology to continuously innovate financial business models and update the industry ecology, giving rise to a digital financial industry with both digital and financial attributes. The use of big data, computing, blockchain, and other technologies will greatly simplify the process of enterprises' access to financial services and improve the efficiency of financial services (Ozili, 2018); digital finance can provide more possibilities for the innovation of financial products through the use of emerging digital technologies, creating new business opportunities and models; digital finance can get rid of geographical constraints and enhance risk assessment capabilities, thus effectively taking into account the long-tail group and providing financing to micro and small enterprises at a lower cost (Wang et al., 2024).

Digital finance is a product of the close integration of digital technology and the financial industry, with similar concepts such as "fintech" and "internet finance". Fintech is considered to describe the innovations made by all businesses seeking to optimize the process, delivery, and use of financial services (Wang et al., 2024), and some scholars consider fintech to be a new financial industry that applies technology to improve financial activities; ten departments, including the People's Bank of China and Cyberspace Administration of China, define Internet finance as a new financial business model in which traditional financial institutions and Internet enterprises use Internet technology and information and communication technology to realize capital financing and complete payment, investment and information intermediary services. The definition of digital finance is more extensive compared to financial technology and Internet finance, which is the expansion and deepening of Internet finance and financial technology. According to the study, digital finance describes the digitalization of the financial industry in general, including all electronic products and services of the financial sector (Gomber et al., 2017). Drawing on the previous research, this paper defines digital finance as the digitization of the financial industry covering all electronic products and services in the financial sector, as well as mobile applications. It is a new financial paradigm that has greatly contributed to the financial sector.

The continuous development of digital finance has innovated a large number of financial products, reconstructed the financial business and business model, and its technology and concepts have penetrated into all walks of life in society, exerting a far-reaching impact on economic development. Existing research on digital finance can be roughly categorized into three prongs. First, at the individual level, scholars have studied the income gap (Yao & Ma, 2022), household consumption (Li et al., 2020), and consumption upgrading, mainly examining the impact of digital finance on the lives of the residents as well as the benefits brought by digital finance; second, at the enterprise level, studies focus on ESG (Mu et al., 2023), corporate financial performance, service-oriented development of manufacturing (Chen & Zhang, 2021), investment in small and micro enterprises (Lin et al., 2022), and structural driving effects on strategic emerging enterprises (Tang et al., 2022); finally, a large number of studies have focused on the social dimension, with fintech, carbon efficiency, green innovation (Lin & Ma, 2022), urban innovation (Li et al., 2023), and the mitigation of information asymmetry by digital finance (Demertzis et al., 2018). It demonstrates great potential for policymakers to utilize digital finance to promote national economic growth and is highly instructive.

Although there have been many studies on the impact of digital finance, little literature has focused on the impact of digital finance on the development of urban green economy. With the acceleration of world economic integration, environmental protection has become one of the major concerns of the international community, under which the United Nations Framework Convention on Climate Change (UNFCCC) was adopted in 1992, the Kyoto Protocol was adopted in 1997, and the Equator Principles were proposed by global financial institutions in 2002 (Li et al., 2018). While transforming the traditional financial industry, digital finance covers the platform economy and green economy, with significant green characteristics. A small amount of literature has explored the mechanism of digital finance's impact on the environment, but consistent conclusions are not reached. On the one hand, the growth of digital finance will lead to an increase in residents' consumption capacity, easier access to financial products and services, and a rapid increase in the consumption of energy-intensive appliances such as air conditioners and cars (Le et al., 2020); digital finance will also provide enterprises with more sufficient funds to expand production, thus increasing energy consumption and carbon dioxide emissions (Cheng et al., 2023). On the other hand, digital finance protects the environment by alleviating financing constraints and the misallocation between supply and demand for investment in green innovations (Feng et al., 2022), enabling companies to afford energy-efficient production technologies and less-polluting equipment at lower costs. Financial development can also reduce carbon dioxide (CO_2) emissions by leveraging the growth of the financial market in the renewable energy sector (Kim & Park, 2016). Therefore, as a result, there are different views in the existing literature on the impact of digital finance on the green economy, and precisely this is the question that this paper needs to answer.

In general, more research topics remain to be explored. Firstly, there are relatively few studies on the impact mechanism of digital finance on GTFP, which can serve as a more comprehensive measure of the quality of green economy development. Nevertheless, the impact mechanism of digital finance on urban green total factor is still a black box. Secondly, for the study of digital finance on GTFP, most of the existing literature is from a global perspective, without considering the differences in the level of digital finance and the differences in geographic regions, failing to give differential consideration to the digital financial empowerment of GTFP. Thirdly, the existing literature ignores a very important factor and fails to take the spatial factor into consideration. Therefore, the marginal contributions of this paper are: first, it adopts data from prefecture-level cities to explore the three mechanisms of technological innovation, industrial structure upgrading, and regulating resource misallocation; second, it considers heterogeneity based on regional geographic differences and financial level differences, while taking policy factor into account, and it explores the heterogeneity before and after the introduction of the G20 High-level Principles for Digital Financial Inclusion issued by the People's Bank of China in 2016; third, considering that GTFP may have possible spatial spillover effects in terms of geographic location or socio-economic aspects, this paper successively constructs a spatial adjacency matrix and a spatial economic-geographic weighting matrix, utilizes the LM test, and adopts the SEM to examine the impact of digital finance on GTFP, to make the empirical results more accurate.

The remaining part of the paper is organized as follows: Section 2 analyzes the logical mechanism between digital finance and GTFP and gives a series of research hypotheses; Section 3 specifies the index system, data sources, and model design of this paper; Section 4 conducts an empirical analysis, which describes and analyzes the impacts of digital finance and GTFP, and conducts a series of robustness tests; Section 5 conducts a mechanism test, utilizing the mediation model to examine the role of digital finance in affecting GTFP; Section 6 conducts spatial econometric analysis, using a spatial geographic weight matrix as well as a spatial adjacency matrix and SEM to validate the spatial spillover effect; Section 7 concludes the paper and proposes some suggestions.

2. Theoretical Analysis and Research Hypothesis

Digital finance belongs to finance in essence, and it can utilize a variety of digital technologies to empower the traditional financial industry and then promote GTFP. Digital finance has significant green features compared with traditional finance. Digital finance has a stronger connection with sustainable development than traditional finance, as it combines traditional financial services such as payment, credit, securities, insurance, etc., with digital technology to develop a new form of convenient and efficient online financial services. For individuals, digital finance saves the time and cost of customer travel. For example, Alipay reduces the need for offline shopping and travel shopping, then reduces the need for car travel (Rosqvist & Hiselius, 2016), and reduces energy consumption in the paper printing and transportation process within the financial industry, thus protecting the environment and increasing GTFP; at the same time, digital finance broadens the public's access to credit resources, and people are more likely to purchase energy-intensive appliances as well as high-carbon-emitting transportation (Le et al., 2020), potentially impacting the growth of GTFP. For companies, on the one hand, digital finance reduces information asymmetry, which can reduce adverse selection and moral hazard and relax financing constraints, thus promoting the continued development of the renewable energy sector and providing financial support for companies' green innovations; on the other hand, digital finance promotes economic growth, and companies could expand their production with more easily accessible credit resources, thus increasing carbon emissions and energy consumption (Cheng et al., 2023), which further hampers the development of the green economy. Based on the multifaceted impact of digital finance on green economy, this paper proposes two possible hypotheses.

H1a: Digital finance significantly contributes to GTFP.

H1b: Digital finance hinders GTFP.

This paper mainly examines the impact of digital finance on GTFP in three pathways: technological innovation, industrial structure upgrading, and resource misallocation mitigation.

First, digital finance promotes technological innovation and indirectly affects GTFP. Digital finance has relaxed the financing constraints of enterprises and effectively lowered the entry threshold for technological innovation. For MSMEs, technological innovation is one of the critical tools for enterprises to improve market competitiveness, while the R&D and technological innovation are accompanied by unknown risks and a large amount of capital investment. However, MSMEs are often not supported by traditional financial institutions due to small asset size and financial opacity. While MSMEs are important contributors to China's GDP and a major creator of jobs, they are also the source of industrial pollution, so MSMEs have great potential for facilitating the development of a green economy. When digital finance utilizes big data, artificial intelligence and other technologies to build an intelligent credit service platform, excessive borrowing costs for MSMEs based on risk control requirements are canceled by financial institutions, thus easing the financial pressure faced by MSMEs in technological innovation and investing more in innovation rather than blindly in production. At the same time, for large enterprises, the development of digital finance reduces service costs for large enterprises, provides more diverse financial products, and prompts enterprises to R&D new technologies and introduce new equipment. Companies will increase their long-term R&D investment due to the reduction of financing constraints (Aghion et al., 2012), and ultimately, through technological innovation, enterprises facilitate carbon reduction (Chen et al., 2024; Sun et al., 2024), improve their resource utilization efficiency, and gradually transform into environmentally friendly, technology-intensive enterprises under the guidance of the policy, thus enhancing GTFP.

H2: Digital finance advances technological innovation, indirectly contributing to GTFP.

Second, digital finance promotes the upgrading of industrial structure. Digital finance is a new direction and new trend of digital technology empowering traditional financial development, and is an important driving force and key support for industrial structure upgrading. On the one hand, digital finance effectively alleviates information asymmetry and information barriers, which are major obstacles to financing for small and micro enterprises, and also major obstacles for traditional finance to promote industrial structure upgrading. Lenders face the problem of adverse selection, and in order to cope with the potentially high risk, financial institutions tend to put forward a higher interest rate for the loan. In contrast, digital finance makes the information of the borrowers and lenders more transparent and safer, giving full play to the financial industry's function of blood transfusion to meet the green and high-tech enterprises' capital needs. As a result, production is shifted from low value-added enterprises to high value-added enterprises, promoting the upgrading of the industrial structure of the society as a whole and the development of the green economy (Du & Li, 2019). On the other hand, digital finance leverages the capital market's mechanism of "survival of the fittest" to optimize the industrial structure. The capital market is a key factor in the stable growth of the economy and the upgrading of the industrial structure. Capital scarcity is a major obstacle to improving energy efficiency (Apeaning & Thollander, 2013), while digital finance improves market transparency through digital credit and other means, and utilizes technologies such as big data and artificial intelligence to guide capital to flow to high-value-added green and sustainable enterprises, thus enhancing GTFP.

H3: Digital finance promotes industrial structural upgrading, indirectly contributing to GTFP.

Finally, digital finance could mitigate resource misallocation. The existing resource mismatch phenomenon in the past makes it difficult for manufacturing enterprises to improve output efficiency and get rid of resource and energy constraints, which is not conducive to the improvement of expected output and the reduction of non-expected output, and thus causes the loss of GTFP. Nevertheless, digital finance has transformed resource allocation, shifting it from a reliance on geographic or physical space to a more efficient process conducted in virtual space, where algorithms are employed to optimize the distribution of resources; besides, digital technology allows financial institutions to better assess the credit level and repayment ability of the borrower, significantly reducing the problem of adverse selection and moral hazards caused by insufficient information (Chari et al., 2014); at the same time, regulators can better perform their regulatory duties supported by digital technologies, reduce rent-seeking behavior, and promote more efficient use of resources (Wang & Shao, 2024). Efficient resource allocation can ultimately promote technological innovation and industrial structure upgrading of the whole city, and improve GTFP.

H4: Digital finance mitigates resource misallocation, indirectly contributing to GTFP.

According to Tobler's First Law of Geography, "All things are related, but nearby things are more related than distant things" (Tobler, 1970). Through applying digital technology, digital finance not only influences the GTFP of the city, but also breaks the spatial limitation and strengthens the spatial effect of finance and GTFP. On the one hand, digital financial inclusion can optimize the allocation of credit, and improve the utilization rate of funds to support the transformation and upgrading of enterprises. It can also provide residents with small loans to drive the economic development of the city, which in turn attracts the transfer of talents, enterprises, technologies, and other resources from surrounding areas to the city (Wang et al., 2022), restricting the development of low-carbon and GTFP in the surrounding areas. On the other hand, digital finance could promote technological innovation, and advanced technology and production methods can radiate and drive the development of neighboring cities, thus driving the growth of GTFP in the whole region.

H5: Digital finance has spatial spillover effects on GTFP.

3. Materials and Methods

3.1 Data Sources

In this paper, 278 prefecture-level cities in China are selected to construct the panel dataset from 2011 to 2021, in which missing values are filled in by the difference interpolation. The city data are mainly from the National Bureau of Statistics of China, the China City Statistical Yearbook, the Statistical Yearbook of Prefecture-Level Cities in China, the Peking University Digital Financial Inclusion Index of China, and the Industrial Development Research Center of Fudan University.

3.2 Definition of Variables and Descriptions

Explained variable: GTFP. The GTFP measure selects the widely-used Super-SBM-Malmquist. The SBM method was first conceptualized and proposed by Tone (2002), which set slack variables in the target function to effectively offset the deficiency caused by the error of slack variables, and then the Super-SBM model was proposed in 2002, which provides a method to compare the efficiency of effective samples on the basis of measuring the efficiency values of different samples. The Malmquist index was first proposed by Malmquist S. in 1953 to study the dynamics of the consumption bundle in the indifference curve of the consumption function, and has been developed and commonly used by later generations in energy (Woo et al., 2015), economics (Lin & Du, 2015), agriculture and forestry (Lin & Fei, 2015), etc.

The input indexes in this paper are divided into capital inputs and labor inputs, where capital inputs are measured with reference to Berlemann & Wesselhöft (2014) using the perpetual inventory stock method with the following formula:

$$K_{i,t} = I_{i,t-1} + K_{i,t-1}(1-\theta) \tag{1}$$

Table 1. Definition of variables and sources

Types of Variables	Variable	Initials	Measurement
Dependent variable	GTFP	GTFP	Super-SBM-Malmquist Method is adopted to measure the GTFP of the city
Independent variable	Digital financial Inclusion index	Index	Choose the "Peking University Digital Financial Inclusion Index of China" and its three sub-indexes (2011-2021)".
	Coverage breadth	Breadth	
	Usage depth	Depth	
	Digitization level	Digit	
Control variables	Economic development	Lngdp	The logarithm of GDP per capita plus one
	Opening up	Open	Total volume of import and export as a percentage of the city's GDP
	Financial development	Fin	Deposit and loan balances of financial institutions as a percentage of the city's GDP
	Government expenditure	Gov	General public budget expenditure as a share of the city's GDP
	Foreign direct investment	Fdi	Foreign direct investment as a percentage of the city's GDP
	Human capital	Edu	Students enrolled in general higher education as a percentage of total population of the city
	Infrastructure	Lnfac	The logarithm of road area per capita plus one
	Industrial structure	Ind	Value added of the secondary sector as a percentage of GDP
	Urbanization level	Urb	The logarithm of population density (people per square kilometer) plus one
	Employed population	Lab	Ratio of employed population to total population
	Fixed investments	Inv	Ratio of investment in fixed assets to GDP
	Fiscal freedom	Fiscal	The ratio of general public budget revenue to. general public budget expenditure

where, $K_{i,t}$ denotes the physical capital stock of city *i* in year t, $I_{i,t-1}$ is the gross investment of city *i* in year *t*-1, θ is the depreciation rate, which is set to 9.6% in this paper, the fixed asset price index of each year is converted to the constant price of 2004, and the capital stock of the base period is calculated based on the total investment in fixed assets. Labor inputs use the number of people employed at the end of the year in the city.

Index of output variables in this paper. Output variables include desirable and undesirable outputs. Desirable output is calculated in terms of GDP converted at constant 2004 prices; non-desired output includes wastewater emissions, sulphur dioxide emissions, and dust and fume emissions.

Explanatory Variable: Digital Financial Inclusion Index. This study draws on existing literature (Li et al., 2023) and adopts the "Peking University Digital Financial Inclusion Index of China" compiled by the Digital Finance Research Center of Peking University in cooperation with the Ant Group Research Institute, and its three sub-dimensions, "Coverage Breadth", "Usage Depth" and "Digitization Level" (2011-2021), as explanatory variables in this paper. To make the results more intuitive, this paper divides the digital financial inclusion index and the three sub-dimensions by 100 as the data.

Control variables: Refer to the previous research (Lei et al., 2023), the following 12 control variables are added to the regression of this paper: Degree of Economic Development (lngdp), Degree of Opening Up (open), Financial Development Level (fin), Government Expenditure Level (gov), Level of Foreign Direct Investment (fdi), Human Capital (edu), Infrastructure (lnfac), Industrial Structure (ind), Urbanization Level (urb), Employed Population (lab), Fixed Investments (inv) and Fiscal Freedom (fiscal).

The definition of variables and sources in Table 1, and the descriptive statistics of the above variables can be found in Table 2.

Table 2. Descriptive statistics of variables

Variable	Obs	Mean	Std. Dev.	Min	Max
GTFP	3091	0.303	0.145	0.032	1
Index	3695	1.814	0.729	0.259	3.28
Breadth	3695	1.727	0.751	0.064	3.378
Depth	3695	1.76	0.727	0.181	3.189
Digit	3695	2.196	0.816	0.168	3.367
Lngdp	3164	10.748	0.576	9.091	12.141
Open	3156	0.172	0.271	0.001	1.785
Fin	3196	2.535	1.188	0.897	7.482
Gov	3196	0.211	0.123	0.071	1.017
Fdi	2912	0.018	0.017	0	0.089
Edu	3205	0.019	0.025	0	0.13
Lnfac	3695	2.444	1.087	0	3.826
Ind	3183	0.452	0.11	0.129	0.746
Urb	3227	5.653	1.115	0	7.748
Lab	2825	0.173	0.288	0.005	2.469
Inv	3196	0.736	1.437	0	9.956
Fiscal	3196	0.449	0.222	0.072	1.038
After	3695	0.453	0.498	0	1
DEM	3695	1.814	0.7	0.493	2.83
Tech	3695	19.871	68.215	0	654.783
Uis	3205	2.302	0.145	1.9	2.733
DEC	3695	0.5	0.5	0	1
RRMindex	3204	0.687	0.598	0	4.179

4. Model Construction

Considering the cumulative effect of GTFP, this paper constructs a dynamic panel model to test.

The basic test model is as follows:

$$GTFP_{i,t} = \alpha_0 + \alpha_1 GTFP_{i,t-1} + \alpha_2 index_{i,t-1} + \alpha control_{i,t} + \tau_i + \pi_t + \varepsilon_{it} \tag{2}$$

In Eq. (1), the subscript i denotes city i, and t denotes year t. $GTFP_{i,t}$ denotes the GTFP of city i in year t; α_0 is a constant term, α_1 is the coefficient of GTFP lagged by one period; α_2 is the coefficient of $index_{i,t-1}$. The explanatory variable index is lagged by one period in this paper to attenuate the bi-directional causality problem; $\alpha control_{i,t}$ is the control variable and coefficient; τ_i is the fixed effect of city, π_t is the fixed effect of time; and $\varepsilon_{i,t}$ is the random disturbance term.

In order to further investigate the role of digital finance in GTFP, this paper builds Eqs. (3) and (4), drawing on the stepwise regression test of:

$$M_{i,t} = \beta_0 + \beta_1 M_{i,t-1} + \beta_2 index_{i,t-1} + \beta control + \tau_i + \pi_t + \varepsilon_{i,t} \tag{3}$$

$$GTFP_{i,t} = \gamma_0 + \gamma_1 GTFP_{i,t-1} + \gamma_2 index_{i,t-1} + \gamma_3 M_{i,t} + \gamma control_{i,t} + \tau_i + \pi_t + \varepsilon_{i,t} \tag{4}$$

In Eq. (3), the mediators $M_{i,t}$ include tech, uis, and RRMindex, examining the effect of $index_{i,t}$, the one-period lagged explanatory variables, on the three mediators; Eq. (4) examines the joint effect of $index_{i,t-1}$, the one-period lagged explanatory variables, and the mediators $M_{i,t}$ on the dependent variables $GTFP_{i,t}$, and the mediating effect holds if the explanatory variable's coefficient γ_2 is less than α_2.

5. Results

5.1 Benchmark Regression Analysis

As shown in Table 3, the benchmark regression results present the contribution of the digital financial inclusion index and the three secondary indexes to GTFP. From column (1) of Table 3, it can be seen that the coefficient of the digital financial inclusion index is 0.2136, which is significant at a 1% significance level, indicating that the development of digital financial inclusion can significantly enhance urban GTFP.

Table 3. Benchmark regression

Variables	(1) Index	(2) Breadth	(3) Depth	(4) Digit
L.GTFP	0.2189^{***}	0.2452^{***}	0.2199^{***}	0.2225^{***}
	(0.0436)	(0.0458)	(0.0465)	(0.0433)
L.index	0.2136***			
	(0.0446)			
L.breadth		0.0853^{*}		
		（0.0431）		
L.depth			0.1186^{***}	
			(0.0265)	
L.digit				0.0474^{***}
				（0.0156）
Cons	0.2492	0.2814	-0.0246	0.0584
	(0.5133)	（0.4369）	（0.5140）	（0.5241）
Control variables	Yes	Yes	Yes	Yes
Region fixed	Yes	Yes	Yes	Yes
Time fixed	Yes	Yes	Yes	Yes
Obs	2,330	2,359	2,330	2,330
R^2	0.4874	0.4605	0.4887	0.4223

Note: ***, ** and * represent significance levels of 1%, 5%, and 10%, respectively; "()" is the standard error

As can be seen from Table 3, the coefficient of coverage breadth of the three secondary indexes of digital financial inclusion is 0.0853, which is significant at the 10% level; the coefficient of usage depth is 0.1186, which is significant at the 1% level; and the coefficient of digitization level is 0.0474, which is significant at the 1% level. This indicates that the three secondary indexes contribute to GTFP to different degrees, with varied impacts. Among them, usage depth has a greater impact on GTFP than coverage breadth and degree of digitization. The possible explanation is that the development of digital finance has passed the stage of expansion and popularization in a simple and crude way, and the demographic dividend has begun to fade away, entering the in-depth development stage. With the continuous emergence of diversified financial services and the popularization of financial knowledge on the internet, digital finance keeps deepening, further enhances the efficiency of resource allocation and improves GTFP.

5.2 Robustness Test

The instrumental variable approach, as the basic solution to endogeneity, can address a wide range of endogeneity problems that violate classical linear regression assumptions, such as the omitted variables, selection bias, bi-directional cause and effect, and measurement error. The instrumental variable approach solves endogeneity problems by finding one or more variables that are correlated with the explanatory variables and not correlated with the model error term in a two-stage regression. In this paper, Geographic Information System (GIS) is used to measure the spherical distance from the host city to Hangzhou (IV1) and the distance from the host city to the capital city of the host province (IV2). Due to the huge difference between the distance and the other variables in terms of magnitude, 10,000 kilometers are used in this paper as the raw data. As the distance is cross-sectional data, we refer to Zhao & He (2022) and others to interact with the instrumental variables with the mean of the digital financial inclusion index, except for this city (DEM), so as to obtain the instrumental variables of the digital financial inclusion index: $IV1 \times DEM$and$IV2 \times DEM$.

The reasons for selecting the above instrumental variables in this paper are as follows: First, in terms of relevance, Hangzhou is the birthplace of China's digital finance. According to the data issued by the research group of the Institute of Digital Finance Peking University in 2021, Hangzhou's digital financial inclusion index has ranked first for many years. Hangzhou has a large number of enterprises that have a leading position in digital finance, such as Ant Financial Services, as well as influential scientific research platforms, such as Zhejiang University and Alibaba's Damo Academy. Meanwhile, a provincial capital is usually the economic center of a province, which gathers talents and innovative activities together and could radiate and drive the development of neighboring cities.

Second, the instrumental variables need to fulfill the exogeneity requirement, i.e., the instrumental variables can only affect GTFP by influencing the digital financial inclusion index. It is known that geographic distance does not directly affect GTFP, and that the average value of the digital finance index other than the city does not affect the GTFP of a single city.

Table 4 Column (1) and Column (2) show the first and second stages of instrumental variable $IV1 \times DEM$. Table 4 Column (3) and Column (4) shows the first and second stages of instrumental variable $IV2 \times DEM$. Both instrumental variables obtained from the two distances show negative coefficients and are significant at 1% in the first stage, so the further away from Hangzhou and the capital city, the lower the digital financial inclusion index of the city, reflecting a significant negative correlation; in the second stage of the two instrumental variables, the digital financial index is still positively correlated to the GTFP and is significant at a 1% level, which indicates that the conclusions of the benchmark regression are robust.

Table 4. Robustness test

Variables	2SLS		2SLS		DID
	(1) L.index	(2) GTFP	(3) L.index	(4) GTFP	(5) GTFP
$IV1 \times DEM$	-0.6686***				
	(0.0434)				
$IV2 \times DEM$			-1.4621***		
			(0.1482)		
L.index		0.4445***		0.7097***	
		(0.0729)		(0.1513)	
L.GTFP	0.0888***	0.2029***	0.0791***	0.1775***	
	(0.0118)	(0.0385)	(0.0129)	(0.0448)	
DEC*After					0.0820***
					(0.0113)
Cons	3.2291***	-0.8906***	3.0408***	-1.6901***	0.3462***
	(0.0278)	(0.2202)	(0.0194)	(0.4522)	(0.0052)
Control variables	Yes	Yes	Yes	Yes	Yes
Region fixed	Yes	Yes	Yes	Yes	Yes
Time fixed	Yes	Yes	Yes	Yes	Yes
Obs	2,810	2,810	2,810	2,810	3,091
R^2	0.9954	0.6723	0.9946	0.6522	0.3455

Note: ***, ** and * represent significance levels of 1%, 5%, and 10%, respectively; "()" is the standard error

The 11th G20 Summit was held in Hangzhou, China, on September 4-5, 2016. The G20 Summit greatly accelerated the use of digital technology and promoted the popularization of financial services, and the first international common agenda for digital financial inclusion - the G20 High-Level Principles for Digital Financial Inclusion (hereinafter referred to as the "Principles") was put forward, which contains 8 principles and 66 recommendations on "advocating the use of digital technology to promote financial inclusion development". The principles solve many existing problems, such as how to support the development of digital finance, how to balance risk and innovation, how to effectively regulate, how to protect the legitimate rights and interests of financial consumers, etc., which is of far-reaching significance to the healthy development of digital finance. Under the guidance of the principles, the development speed and quality of digital finance in various regions have been increased or optimized to different degrees. Among them, cities with advanced digital technology are more likely to burst with innovation vitality stimulated by the policy because of rich network resources and gathering of talents, etc. Meanwhile, the advanced digital technology also lays a solid foundation for its further expansion and in-depth development. Cities with backward digital technology are dragged down by the lack of resources in their response speed to the policy. Therefore, this paper takes the median of the digital financial inclusion index released by the principles in 2015 as the boundary, divides cities into high-level digital finance cities and low-level digital finance cities, and designates high-level digital finance cities as the experimental group and low-level cities as the control group.

The DID model is constructed as follows:

$$GTFP_{i,t} = \alpha_0 + \alpha_1 DID + \alpha_2 After_t + \alpha_3 DEC_i + \alpha control_{i,t} + \tau_i + \pi_t + \varepsilon_{i,t} \quad (5)$$

$After_t$ is a dummy variable. According to the Principles released, the year after 2016 is set to be 1 and 0 vice versa; DEC_i indicates whether city i is a treatment group, taking 1 if it is and 0 vice versa; DID is the interaction term of $After_t$ and DEC_i.

Column (5) of Table 4 presents the estimation results of DID, and the coefficient of DID is significant at the 1% level, indicating that the release of the principles has a significant contribution to the GTFP of high-level digital finance cities.

The parallel test is a prerequisite for addressing endogeneity using the DID model. The parallel test fictionalizes the time of policy implementation, and if the treatment group and the control group have the same trend before policy implementation, it proves that the conclusions of the ensuing DID method are robust, not a bias caused by the model setting or sample selection. In this paper, the parallel test is conducted by replacing. $After_t$ with the dummy variable. The results are shown in Figure 1, indicating that there is no significant difference between the treatment group and the control group before the policy implementation, and the parallel hypothesis is satisfied.

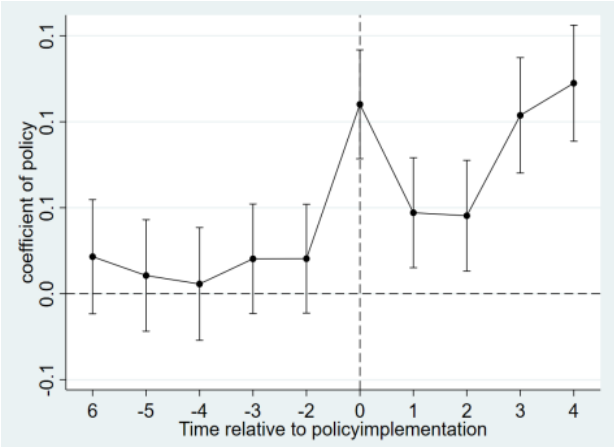

Figure 1. Parallel test

In this paper, random samples are taken as the treatment group for regression, and the interaction term DID coefficients are recorded 500 times to simulate the estimation results without policy influence. Figure 2 shows that the regression coefficients are roughly normally distributed, and a large number of sample points have regression coefficients clustered around 0, which is far from the true DID coefficient of 0.0820, and most of the sample coefficients are not significant at the 10% level. This indicates that the effect of the principles on urban GTFP is not affected by other unknown factors.

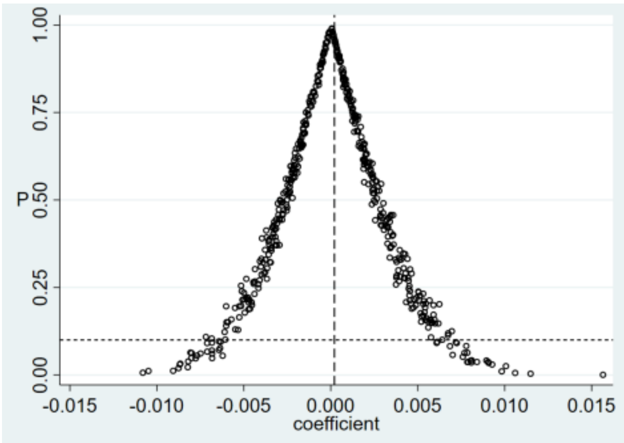

Figure 2. Placebo test

5.3 Heterogeneity Test

First of all, considering that China is a vast country, and there is a huge gap between the east, the central and the western parts of the country in terms of economic environment, geographic location, infrastructure, etc., this paper examines the regional heterogeneity of the impact of digital finance on GTFP by dividing China into the east, the central and the western regions in terms of geographic location. As shown in Table 5, the coefficient of improvement of digital finance development on GTFP in the central and western regions is larger and more significant, which may indicate that the central and western regions are benefiting from the rapid expansion of digital finance at the initial stage, and utilizing the inclusive characteristics of digital finance to develop the green economy. While the eastern regions are developing at a faster pace, and the marginal benefits of digital finance are beginning to diminish, which requires in-depth development of digitization.

Table 5. Regional heterogeneity test

Variables	East	Middle and West
L.index	0.1277* (0.0669)	0.1703*** (0.0590)
L.GTFP	0.1344** (0.0526)	0.2371*** (0.0576)
Cons	0.0311 (1.0563)	0.2812 (0.4288)
Control variables	Yes	Yes
Region fixed effect	Yes	Yes
Time fixed effect	Yes	Yes
Obs	937	1377
R^2	0.3558	0.2168

Note: ***, ** and * represent significance levels of 1%, 5%, and 10%, respectively; "()" is the standard error

Table 6. Heterogeneity test for financial development level

Variables	High	Low
L.index	0.1951*** (0.0529)	0.2685*** (0.0865)
L.GTFP	0.1591** (0.0663)	0.2576*** (0.0642)
Cons	0.2101 (0.7440)	-0.6949 (0.8953)
Control variables	Yes	Yes
Region fixed effect	Yes	Yes
Time fixed effect	Yes	Yes
Obs	1186	1144
R^2	0.4213	0.1866

Note: ***, ** and * represent significance levels of 1%, 5%, and 10%, respectively; "()" is the standard error

Table 7. Tests for temporal heterogeneity (2011-2016)

Variables	(1) Index	(2) Breadth	(3) Depth	(4) Digit
L.index	0.0261 (0.0316)			
L.breadth		-0.0620 (0.0574)		
L.depth			0.0227 (0.0260)	
L.digit				0.0086 (0.0072)
L.GTFP	0.3110*** (0.0560)	0.3108*** (0.0557)	0.3096*** (0.0569)	0.3112*** (0.0557)
Cons	0.5075 (0.5386)	0.4379 (0.5340)	0.4517 (0.5421)	0.4960 (0.5360)
Control variables	Yes	Yes	Yes	Yes
Region fixed effect	Yes	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes	Yes
Obs	1200	1200	1200	1200
R^2	0.3797	0.3505	0.4230	0.3741

Note: ***, ** and * represent significance levels of 1%, 5%, and 10%, respectively; "()" is the standard error

Second, the financial development level of the city may also affect the contribution of digital finance to GTFP. On the one hand, cities with a higher financial development level enjoy stronger innovation vitality, better infrastructure, more talent gathering, and more capital. As a result, more financial institutions tend to integrate and develop the digital technology, and then promote the green economy; on the other hand, cities with lower financial development level tend to absorb the emerging digital technology. The inclusive characteristics of digital finance can greatly expand the customer base of the financial industry, reduce the information asymmetry, rationalize credit resources utilization of the financial industry, and contribute to the promotion of GTFP. In this paper, 278 cities are divided into low-level cities and high-level cities based on the median of financial development level, and the regression results are shown in Table 6: the coefficient of low-level cities is larger and significant at a 1%

level, which indicates that it is easier to exert the green effect of digital finance at low-level cities.

Finally, the paper examines the impact of different periods on GTFP. As shown in Table 7 and Table 8, the coefficients of the index and the three secondary indexes of breadth, depth, and digit are all insignificant from 2011 to 2016, while the coefficients are all positive from 2017 to 2021, and all of them are significant at the 1% level, which suggests that the green effect of digital finance is gradually enhanced. Among them, the coefficient of coverage breadth was negative during 2011-2016, indicating that digital technology was disorderly expanded in the financial industry from 2011 to 2016, leading to a waste of resources, but this situation was alleviated during 2017-2021.

Table 8. Tests for temporal heterogeneity (2017-2021)

Variables	(1) Index	(2) Breadth	(3) Depth	(4) Digit
L.index	0.3819^{***} (0.0669)			
L.breadth		0.3146^{***} (0.1024)		
L.depth			0.1922^{***} (0.0561)	
L.digit				0.0905^{***} (0.0190)
L.GTFP	-0.3336^{***} (0.0304)	-0.3151^{***} (0.0312)	-0.3309^{***} (0.0304)	-0.3312^{***} (0.0310)
Cons	-2.2657^{*} (1.1886)	-1.9998^{*} (1.1781)	-2.1607^{*} (1.1735)	-2.0178^{*} (1.1317)
Control variables	Yes	Yes	Yes	Yes
Region fixed effect	Yes	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes	Yes
Obs	1130	1130	1130	1130
R^2	0.3780	0.3416	0.3594	0.3381

Note: ***, ** and * represent significance levels of 1%, 5%, and 10%, respectively; "()" is the standard error

5.4 Analysis of Impact Mechanisms

The mediators selected in this paper are as follows: the Technological Innovation Level (tech), drawing on the China City and the Industry Innovation Index released by the Industrial Development Research Center of Fudan University to measure the technological innovation index of China's prefectural-level cities from 2011-2021; The Upgrading of Industrial Structure (uis) is measured using the value added of the three major industries in each city, which is as follows:

$$uis = \sum_{i=1}^{3} I_i \times i \tag{6}$$

where, I_i is the proportion of the added value of industry i to the city's GDP for the year; the Relative Resource Misallocation Index (RRM index), is constructed by the capital misallocation index and labor misallocation index, in the way of principal component analysis.

Table 9 presents the estimation results with the technological innovation level as the mediator. The coefficient of the one-period-lagged index in the second column of the regression results is 15.0343 and is significant at the 1% level, indicating that the improvement of the digital finance level has significantly promoted the urban technological innovation level; in the third column, the regression coefficient of the one-period-lagged index on the GTFP is significant at the 1% level and the coefficient is 0.1640, which is smaller than that of the one-period-lagged index in the first step of the baseline regression, so the mediating effect of the technological innovation level is significant, and digital financial inclusion can promote urban GTFP through the technological innovation level.

Table 10 shows the results of regression with the upgrading of industrial structure as the mediator. The coefficient of the one-period-lagged index in the second column of the regression results is 0.0422 and is significant at the 1% level, indicating that the development of digital finance also has significantly optimized industrial structure; at the same time, the regression coefficient of the one-period-lagged index on the GTFP is significant at the 1% level, and the coefficient is 0.2027, which is lower than that in the first column, as shown in the third column of the regression results. So, the upgrading of the industrial structure has a significant mediating effect, and digital financial inclusion can promote urban GTFP through industrial structure upgrading.

Table 9. Technological innovation level

Variables	Baseline Regression	Technological Innovation Level	
	(1) GTFP	(2) Tech	(3) GTFP
L.index	0.2136***	15.0343***	0.1640***
	(0.0446)	(5.5795)	(0.0477)
L.GTFP	0.2189***		0.2043***
	(0.0436)		(0.0449)
L.M		1.0427***	
		(0.0635)	
M			0.0003***
			(0.0001)
Cons	0.2492	5.4513	0.4142
	(0.5133)	(120.1317)	(0.5062)
Control variables	Yes	Yes	Yes
Region fixed effect	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes
Obs	2,330	2,349	2,330
R^2	0.4874	0.9828	0.4531

Note: ***, ** and * represent significance levels of 1%, 5%, and 10%, respectively; "()" is the standard error

Table 10. Upgrading of industrial structure

Variables	Baseline Regression	Upgrading of Industrial Structure	
	(1) GTFP	(2) Tech	(3) GTFP
L.index	0.2136***	0.0422***	0.2027***
	(0.0446)	(0.0102)	(0.0437)
L.GTFP	0.2189***		0.2203***
	(0.0436)		(0.0435)
L.M		0.5389***	
		(0.0443)	
M			0.1649
			(0.1026)
Cons	0.2492	0.6785***	-0.0413
	(0.5133)	(0.1294)	(0.5180)
Control variables	Yes	Yes	Yes
Region fixed effect	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes
Obs	2,330	2,348	2,330
R^2	0.4874	0.8868	0.4688

Note: ***, ** and * represent significance levels of 1%, 5%, and 10%, respectively; "()" is the standard error

Table 11. RRM index

Variables	Baseline Regression	Relative Resource Mismatch Index	
	(1) GTFP	(2) RRM index	(3) GTFP
L.index	0.2136***	-0.3882*	0.2092***
	(0.0446)	(0.2169)	(0.0440)
L.GTFP	0.2189***		0.0155**
	(0.0436)		(0.0071)
L.M		0.6076***	
		(0.0435)	
M			0.0150**
			(0.0070)
Cons	0.2492	-1.2380	0.3308
	(0.5133)	(1.8095)	(0.5254)
Control variables	Yes	Yes	Yes
Region fixed effect	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes
Obs	2,330	2604	2,330
R^2	0.4874	0.4070	0.4837

Note: ***, ** and * represent significance levels of 1%, 5%, and 10%, respectively; "()" is the standard error

In Table 11, the RRM Index is taken as a mediator for regression. The coefficient of the one-period-lagged index in the second column of the regression results is -0.3882, and is significant at the 10% level, indicating that the development of digital finance can effectively alleviate resource misallocation. At the same time, the third column of the regression results shows that the coefficient of a one-period-lagged index on GTFP is significant at the 1% level, and the coefficient is 0.1923, which is smaller than the coefficient of the one-period-lagged index in the first column. The mediating effect of the RRM index is significant, indicating that digital finance can promote urban green economic growth by alleviating resource misallocation.

In summary, the model constructed with Technological Innovation Level, Upgrading of Industrial Structure and RRM Index as mediators verified hypotheses 2, 3, and 4 respectively, proving the indirect impact of digital financial inclusion on GTFP.

5.5 Analysis of Spatial Spillover Effects

From the above regression results of this paper, it can be seen that digital finance strengthens the information acquisition ability of the financial industry, enabling it to better identify the green projects and green loans, reduce the transaction and service costs, promote the technological innovation of cities and industrial structure upgrading, alleviate the misallocation of resources, and promote the growth of GTFP in this city. Theoretically, when digital finance promotes the green economy of the city, it inhibits the neighboring areas' green economy through talents and resources aggregation, or drives its development through the radiation effect. However, the classical measurement is difficult to achieve the expected effect while studying the impact of the green effect of digital finance on neighboring regions. So, this paper incorporates the spatial structure into the analytical model for the spatial measurement.

Firstly, this paper carries out the selection of the spatial matrix. To better measure the relationship between digital finance and GTFP, this paper firstly selects the economic-geographic weight matrix W1 with both geographic and economic attributes and, at the same time, selects the spatial adjacency matrix W2 for comparing. Among them, the economic - geographical weight matrix is obtained by taking the multiplicative inverse of the geographic distance calculated by latitude and longitude, and then interacting with the multiplicative inverse of the absolute value of the GDP difference between cities.

$$W1_{i,j} = \frac{1}{dis_{i,j}} \times \frac{1}{|GDPgaps_{i,j}|} \tag{7}$$

Subsequently, the Moran test is conducted on the index and the GTFP, and the results are shown in Table 12. GTFP and index both have a significant positive correlation during 2011-2021, suggesting a clustering of cities with higher levels of GTFP and higher levels of digital finance development, and the GTFP Moran index is roughly trending upward with increasing spatial dependence.

Table 12. Moran test

Years	W1				W2			
	GTFP		index		GTFP		index	
	Moran's I	Z statistic	Moran's I	Z statistic	Moran's I	Z statistic	Moran's I	Z statistic
2011	0.080***	2.763	0.521***	17.067	0.190***	4.546	0.481***	11.214
2012	0.072**	2.510	0.548***	17.962	0.190***	3.534	0.488***	11.388
2013	0.057**	2.020	0.551***	18.081	0.124***	3.007	0.476***	11.105
2014	0.056**	1.995	0.575***	18.843	0.063***	1.589	0.418***	9.748
2015	0.077***	2.660	0.582***	19.085	0.152***	3.668	0.466***	10.868
2016	0.050*	1.780	0.554***	18.168	0.142***	3.428	0.440***	10.266
2017	0.331***	11.017	0.559***	18.328	0.206***	4.894	0.475***	11.085
2018	0.130***	4.448	0.559***	18.334	0.126***	3.061	0.540***	12.577
2019	0.081***	2.771	0.552***	18.102	0.289***	6.805	0.548***	12.768
2020	0.377***	12.521	0.548***	17.968	0.209***	4.959	0.565***	13.152
2021	0.268***	9.015	0.529***	17.333	0.511***	12.129	0.590***	13.718

Note: ***, ** and * represent significance levels of 1%, 5%, and 10%, respectively; "()" is the standard error

Through the LM test, it was found that the impact of digital finance on GTFP has a spatial error effect when using the economic-geographical weight matrix. The Hausman test is used to establish the SEM and then to estimate the economic-geographical weight matrix, the model is as follows:

$$GTFP_{i,t} = \delta_0 + \delta_1 index_{i,t} + \delta control_{i,t} + \lambda \sum_j w_{i,t} \mu_{i,t} + \tau_i + \pi_t + \varepsilon_{i,t} \tag{8}$$

where, $w_{i,t}$ is a spatial weight matrix element from the economic-geographical weight matrix W1, $index_{i,t}$ is the digital financial inclusion index of city i in year t, $control_{i,t}$ is the corresponding control variable, τ_i is the fixed effect of city, and π_t is the fixed effect of time.

The regression results are shown in Table 13, where the spatial adjacency matrix W2, as a control, is regressed with economic-geographic weight matrix W1 synchronously based on SEM. From the estimation results, it can be seen that the coefficient of λ is positive and significant at the 1% level for both W1 and W2, indicating that the GTFP growth of each city has a strong spatial dependence, and the spillover effect of digital finance for GTFP growth would be stronger if the neighboring city has a better green economy and vice versa. The index coefficients of W1 and W2 are 0.1413 and 0.1454, respectively, and both are significant at the 1% level. Therefore, the development of digital financial inclusion has led to an increase in GTFP in neighboring regions through the radiation effect.

Table 13. SEM estimation

Variables	W1	W2
Index	0.1413***	0.1454***
	(0.0319)	(0.0327)
λ	0.3725***	0.3189***
	(0.0335)	(0.0217)
Control variables	Yes	Yes
Region fixed effect	Yes	Yes
Time fixed effect	Yes	Yes
Obs	2937	2937
R^2	0.0016	0.0042
Log-likelihood	3158.7110	3200.1644

Note: ***, ** and * represent significance levels of 1%, 5%, and 10%, respectively; "()" is the standard error

Comparing the regression of W1 and W2, it can be seen that the spatial spillover effect is larger under economic-geographic weights, indicating that digital finance creates spillovers by compressing geographic distances and enhancing economic linkages, which in turn boosts GTFP. Therefore, as with geographic characteristics, socioeconomic factors are equally important in broadening the scope of benefits of digital finance's impact on green economic growth, and amplifying spatial spillovers requires strengthening interregional economic linkages.

6. Research Findings and Policy Recommendations

Digital financial inclusion, supported by digital technology, has reduced transaction costs, improved operational efficiency, and expanded customer groups for the traditional financial industry, enabling it to better serve the development of GTFP. This paper constructs a two-way fixed effects model based on the data samples of 278 Chinese cities from 2011 to 2021, and then carries out a series of mechanism analyses, robustness analysis, heterogeneity analysis based on regression modeling. It expands the examination of the green effect of digital finance to the spatial level, and constructs a SEM to prove that the promotion of digital finance on urban GTFP has a significant spatial spillover effect, which provides new ideas for the research on digital finance. The empirical results show that: (1) digital finance has a significant promotion effect on GTFP in the city, and can pass the robustness test such as DID, instrumental variable method, placebo test, etc.; (2) digital finance could significantly promote the development of GTFP in the city through the three paths: technological innovation, industrial structure upgrading and alleviation of resource misallocation; (3) The support of digital finance for green economic development in the central and western regions is stronger than that in the eastern region, and the support for cities with a lower financial development level is stronger than that of cities with a higher financial development level, and the green effect in the later part of the sample is stronger than that in the earlier part of the sample; (4) digital finance has a significant spatial spillover effect on the impact on GTFP, and it is related to the economic development level of neighboring cities.

On this basis, the paper proposes several policy recommendations:

Firstly, strongly support the development of fintech enterprises to realize the green economic transformation of the whole society. Digital finance could significantly promote the green economy, so the Chinese government should encourage and support fintech enterprises to increase R&D investment and development and innovate digital financial products. At the same time, the government should actively promote the construction of digital infrastructure, as non-profit and non-competitive infrastructure such as 5G base stations and digital credit systems play a key role in activating market vitality and promoting the green effect of digital technology. However, market has blindness and profit-seeking nature, which brings new data risk and market risk with the rapid development of digital finance. Therefore, it is necessary to establish a comprehensive modern financial regulatory system and keep pace with the times of the digital financial legal system.

Secondly, fully leverage the functions of digital finance in promoting urban technological innovation, upgrading industrial structure, and easing resource misallocation. To begin with, local governments should strengthen their support for green credit, encourage financial institutions to dig deeper into the application fields of digital technology, innovate financial services and financial products, and provide new solutions to the difficulties faced by enterprises in technological innovation, such as difficult and expensive financing. In addition, local government should stick to the upgrade of industrial structure, accurately direct financial resources into the digital industry and support low-energy, low-pollution and innovative enterprises, encourage financial institutions to enhance their risk supervision capabilities, establish a sound risk detection and treatment system, and carry out the all-dimensional digital transformation of traditional industries. Finally, with digital technology, the government should accurately locate the contradiction between the supply and demand of production factors, reducing the friction of production factor flow, improving the allocation efficiency of financial products, and promoting the development of urban GTFP.

Thirdly, coordinate regional development and give full play to regional advantages. The central and western regions are endowed with low land cost and rich natural resources based on which we can lay out data servers at a low price, provide rich computing resources for the eastern region, and explore a new model of "introducing digital technology in the central and western regions and meeting the needs of infrastructure in the eastern region", so as to achieve a win-win outcome. Compared with the eastern region and cities with a higher financial level, the central and western regions and backward cities tend to have higher marginal returns. Digital financial inclusion plays a more significant role in advancing technological innovation, optimizing industrial structure, and alleviating resource allocation, thus accelerating the development of GTFP. In addition, emphasize the exchange of resources such as talents and information technology, and build a collaborative and innovative platform for sharing information technology and talents, so as to fully capitalize on digital finance and form a green growth, collaborative network.

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Data Availability

The data used to support the research findings are available from the corresponding author upon request.

Conflicts of Interest

The authors declare no conflict of interest.

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