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Review

The Effect of Digital Financial Inclusion on Green Total Factor Productivity

Yujie Jiang, Hao Wang*, Li Liu

School of Business, Jinling Institute of Technology, Nanjing 211169, China

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Abstract

As the digital era continues to evolve, digital inclusive finance (DIF) has emerged as a transformative financial service model, significantly enhancing green total factor productivity (GTFP). Leveraging panel data from 30 Chinese provinces (2013–2023) alongside Peking University's Digital Inclusive Finance Index, this study employs a two-way fixed effects model, mediation effect, and two-stage least squares regression to analyze the influence of digital inclusive finance on GTFP and its underlying mechanisms. Key findings reveal that: (1) DIF substantially boosts GTFP growth; (2) in the process of DIF's impact on GTFP, it will cause a decrease in carbon emission intensity (CEI), which indirectly has a positive effect on GTFP; and (3) its economic impact varies significantly across regions and stages of DIF development. These insights shed new light on how DIF can drive sustainable regional development, offering both theoretical and empirical foundations for policymakers pursuing greener economic transformation.

Keywords: DIF, GTFP, green and low-carbon

Introduction

Productivity is the "primary" variable for a country's long-term economic growth (Solow, 1957) [1], and driven by globalization and technological revolution, DIF, as an important achievement of financial innovation, is profoundly influencing the economic landscape of various countries. After 40 years of rapid growth, China is facing multiple challenges, such as the decline of traditional factor dividends, deepening population aging, and constraints of the "dual carbon" target. According to data from its National Bureau of Statistics, the average annual growth rate of labor productivity in China has fallen from 9.5% to 5.7% from 2010 to 2022 (World Bank, 2023). Although there is no unified indicator to measure GTFP, the relevant impact of GTFP is also reflected in it. At the same time, the deep integration of digital technology and inclusive finance is reshaping the way resources are allocated. The China Digital Inclusive Finance Index released by the Digital Finance Research Center of Peking University shows that from 2011 to 2021, the average provincial index will rise from 33 to 341, with an average annual compound growth rate of 26.4%, and the coverage, depth of use, and degree of digitalization will expand exponentially. Whether DFI can become a new driving force for improving GTFP in the dual context of declining "efficiency dividends" and tightening "carbon constraints" has become a major issue that urgently needs to be answered.

*e-mail: wanghao@jit.edu.cn
Tel.: +86-187-9664-5132

DIF can not only promote economic growth and optimize industrial structure but also enhance total factor productivity through technological innovation and resource allocation optimization, thereby promoting high-quality development of the global economy. From an international perspective, there are still 1.7 billion adults in 76 developing countries worldwide who lack formal financial services (Global Findex, 2022). The World Bank estimates that if DFI can increase financial service coverage by 20%, it will significantly enhance the GTFP of these countries. From the case studies of M-Pesa in Kenya and Union Press in India, it can be seen that mobile payments will have a driving effect on the GTFP of enterprises in the region (Jack & Suri, 2021) [2]. However, research on DFI and GTFP in Europe and the United States mostly focuses on microenterprises, lacking macro-level regional evidence and rarely incorporating carbon emission constraints. From a Chinese perspective, on the one hand, China's total carbon emissions reached 11.9 billion tons in 2021, accounting for 33% of the global total, and CEI per unit of GDP is 2.3 times the OECD average level (IEA, 2023); on the other hand, DFI is rapidly penetrating high energy-consuming industries through online credit, green supply chain finance, and carbon account systems. As of June 2023, Ant Group has cumulatively invested 560 billion yuan in "green loans", driving a reduction of 320 million tons of carbon dioxide emissions. Therefore, incorporating CEI into the analytical framework of DFI and GTFP is not only a practical response to its "dual carbon" strategic policy but also a theoretical exploration for China to further improve its modernization path.

DIF also has a solid theoretical basis for its potential impact on GTFP. Romer (1990) emphasized that financial deepening promotes technological progress by reducing innovation costs [3]. Pittman (1983) and Chung et al. (1997) considered pollution emissions as an unexpected output and proposed the concept of GTFP [4-5]. Through their research, they found that DIF reduces CEI through green credit, carbon disclosure, and risk pricing, thereby enhancing GTFP. Through continuous research by later generations, it has gradually been discovered that the impact of DIF on GTFP is not limited to the indirect mechanisms demonstrated, but there are also other mechanisms of action. Its specific manifestation is that DIF comprehensively promotes the improvement of GTFP through various mechanisms, including optimizing resource allocation, supporting technological innovation, managing environmental risks, enhancing financial accessibility, forming policy synergies, providing data-driven decision support, and changing social awareness and behavior. These mechanisms interact to form an organic ecosystem that collectively promotes the development of a green economy. As one of the influencing mechanisms, CEI is continuously declining due to various factors, including the optimization of resource allocation, the reduction of financing thresholds, and technological innovation. A large part of these impacts stems from the technological upgrading and progress of DIF. On the other hand, the decline of CEI can reduce the negative impact of environmental pollution on production activities, while reducing CEI is often accompanied by green technology innovation and industrial upgrading, both of which can improve GTFP. Based on this, this article proposes the following hypothesis:

Hypothesis 1: DIF has a driving effect on improving GTFP

Hypothesis 2: CEI acts as a mediator variable, indirectly leading to DIF having a promoting effect on GTFP

Finally, the dynamic nature of both DIF and environmental challenges requires analysis using recent data. Many existing studies, while valuable, rely on data that may not fully capture the latest developments in DFI and the evolving environmental landscape. The proposed research's use of panel data from 2013–2023 provides a more up-to-date perspective on these rapidly changing phenomena.

Literature

DFI expands financial access through digital means, enhancing services in remote areas. Guo et al. (2020) [6] suggest a nuanced measure for DFI, considering coverage, usage depth, and digitalization, which is crucial for assessing its complex impacts. Other variations, such as the Super-SBM model [7-10] and Stochastic Frontier Analysis (SFA) [11-12], are also employed in the literature to estimate efficiency, sometimes incorporating undesirable outputs to measure "green" efficiency. At present, research on DIF mainly focuses on two aspects: productivity and economic growth. They found that DIF significantly promoted provincial economic growth and urban total factor productivity, and improved accessibility and industrial upgrading (Ahmad et al., 2021; Zuo et al., 2024) [13-15]. At the enterprise level, the research of Zeng and Lei (2021), Li and Tian (2023), Fu and Madini (2024), and Liu et al. (2024) [16-19] also unanimously recognized that the development of DIF has a promoting effect on the improvement of production factors in enterprises.

When measuring GTFP, most existing research requires the inclusion of adverse outputs such as pollution or carbon emissions in efficiency calculations. Studies employ various DEA-based models, including those accounting for undesirable outputs [7-10, 20-26]. Some studies also use the DEA Malmquist index method, which can effectively measure changes in total factor productivity, but cannot take into account the required "unexpected output". Therefore, GTFP is more suitable for capturing "green" productivity efficiency that meets environmental priorities. Studies on GTFP highlight various factors influencing it, including environmental regulation [11, 24, 27], technological progress (including green technology innovation)

[10, 24, 27-30], industrial structure [8, 10, 24, 28, 31], foreign direct investment (FDI) [23-24], and ESG performance [27, 29-30, 32-34].

The nexus between DFI, productivity, and environmental outcomes, particularly in the context of green and low-carbon development, is a more recent but rapidly expanding area of research. Most studies acknowledge the promoting effect of DIF on GTFP, but the research methods and mechanisms are different. Their research focuses mostly on the impact mechanisms of industrial structure, technological innovation, and green finance expansion. Firstly, the impact of DIF on industrial structure is an important influence mechanism on GTFP, which is mainly reflected in the fact that the development of DIF has well supported the development of green new industries, gradually increasing the proportion of green emerging industries in the industrial structure, thereby driving the greening of the industrial structure and promoting the development of various industries and the overall GTFP (Zou et al., 2024; Liu et al., 2024; Xu et al., 2024; Zhang et al., 2024; Shang and Feng, 2024; Wu and Wang, 2025) [14, 35-39]. Another key mechanism by which DIF affects GTFP is technological innovation. Some studies collectively suggest that DFI, by facilitating access to finance and information, can stimulate investment in green technologies and innovation, which in turn can improve the efficiency of green technology [27, 30, 40-45]. In addition, the expansion mechanism of green finance introduces more opportunities and capital investment for greening by expanding the scale of the green finance market, driving the progress and development of green technology, and laying the foundation for the development of GTFP [28, 42, 46-47]. Besides, Zou et al. (2024) [14] and Yi et al. (2025) [48] also highlight resource allocation and human capital as contributing factors.

Although there have been relevant studies on the transmission mechanism of energy efficiency (Liu et al., 2025) [49], most of them appear as analytical components, and targeted research on the transmission mechanism is currently relatively scarce. Some studies directly examine the link between DIF and environmental indicators, such as carbon emissions or green efficiency. Zheng et al. (2023) [50] and Salman & Ismael (2023) [51] show DFI can negatively affect CO_2 emissions, with long-term benefits in some regions. Liu et al. (2023) [52] and Zhang et al. (2022) [41] find similar benefits in China's agriculture and manufacturing. Lee et al. (2022) [53] report enhanced green economic efficiency in Chinese cities but note spatial spillover issues.

Despite the general positive findings, the literature also reveals significant regional heterogeneity and context-specific effects. Due to significant differences in economic structure, resource endowment, policy environment, and development level among different regions, research often emphasizes significant regional heterogeneity in economic and environmental outcomes [7-10, 14-15, 20-23, 27, 40-41, 48, 52-58]. The researchers from Mo et al. (2025) [40] note that DFI has a more muted impact on sustainable economic expansion in China's western and northeastern areas, as well as in certain eco-zones. Ma et al. (2024) [55], focusing on agricultural GTFP, find a dual role of DIF with contrasting effects in eastern and central versus western regions and unique negative spillover effects on nearby regions. Meanwhile, this is also the viewpoint held by most scholars - the promoting effect of DIF on GTFP is more significant in the eastern region, large cities, and areas with complete financial infrastructure (Mo et al., 2025; Jia et al., 2025; Zhu et al., 2023; Zhou et al., 2024) [40, 56-58].

However, the potential trade-off between the two may not only manifest in regional heterogeneity. Ma et al. (2024) [55] found that the impact of DFI on China's agricultural GTFP not only varies by region but is also significantly influenced by the development stage. Lee et al. (2022) [53] also pointed out that DFI may replace pollution. Therefore, it is also important to study the heterogeneous impact of various development dimensions of DIF on GTFP.

In summary, existing literature adopts different methods to analyze the complex relationship between DIF, productivity, and the environment. Firstly, DEA-based methods are very popular in efficiency measurement; secondly, panel data models (including fixed effects, mediation effects, and spatial models) are used for impact analysis, while techniques such as IV/GMM are used to address endogeneity issues. In addition, scholars have combined DEA Malmquist, bidirectional fixed effects, and 2SLS, consistent with established practices in the field, providing a solid foundation for empirical analysis. However, although many studies have explored mechanisms linking DFI with productivity and the environment, a comprehensive understanding of how DFI specifically promotes productivity growth at the provincial city level is still developing. DFI, the interaction between mechanisms such as energy consumption and resource efficiency, as well as their comprehensive impact on total factor productivity while minimizing environmental impact, deserves further research. Therefore, this article will further study the role and impact mechanism of DIF on GTFP based on provincial-level urban panel data.

Experiment

Data Collection

This research utilizes data from 30 mainland Chinese provinces (omitting Hong Kong, Macau, Taiwan, and Tibet) spanning 2013 to 2023, prioritizing data reliability and precision. GTFP serves as the model's dependent variable, while the Peking University Digital Inclusive Finance Index acts as a proxy for measuring DFI. The research empirically examines how DIF influences GTFP. At the same time, to explore potential mechanisms, regional carbon emissions are incorporated as a mediating variable, testing whether DFI affects GTFP by altering emission levels. The analysis also controls for key factors, including regional economic development, industrial structure, fiscal decentralization, capital stock, and urbanization rates, to isolate the model's core relationships. Additionally, to address potential endogeneity concerns, delayed DIF by one period is utilized as an instrumental variable, ensuring more robust causal inference.

GTFP data is primarily sourced from the National Bureau of Statistics' official website, provincial statistical yearbooks and bulletins, as well as the China Statistical Yearbook and China Industrial Statistical Yearbook. Carbon emissions figures were obtained from the European Union's Emissions Database for Global Atmospheric Research (EDGAR). The DIF index is derived from a joint report by Peking University's Digital Finance Research Center and Ant Financial. Control variables and supplementary raw data are collected from the CSMAR, the National Bureau of Statistics' website, the China Statistical Yearbook, and provincial yearbooks. Where gaps exist in the data set, missing values are estimated using linear interpolation.

Variable Measurement

(1) Dependent Variable

This study selects GTFP at the provincial level as the dependent variable. On the one hand, traditional TFP only focuses on economic output efficiency and ignores resource and environmental costs. GTFP incorporates energy input and unexpected output (such as carbon emissions) into the production boundary, which can accurately measure the "real efficiency under unit environmental cost" and is an authoritative indicator for evaluating green and high-quality development (YU et al., 2022) [59]. In the context of China's "dual carbon" policy development, GTFP has become a core variable for policymakers to measure regional green development performance (Liu et al., 2023) [60]. On the other hand, the "green" attributes of DFI are highly coupled with the GTFP enhancement path. Liu et al. (2023) found that DFI provides higher risk tolerance funding for green research and development, promoting progress in green technology [60]. In addition, Zhou and Ye (2023) believe that DFI can reduce corporate financing costs through tools such as green loans and carbon accounts and promote clean technology investment, thereby reducing CEI and enhancing GTFP [61]. Forced innovation is also a mechanism in the process of DIF improving GTFP (Zhang, 2025) [62].

The SBM model is a nonradial, nonangular efficiency measurement method proposed by Tone (2001). The model considers inputs, expected outputs, and unexpected outputs (such as carbon emissions and other environmental factors) and measures efficiency losses through slack variables, which can more accurately reflect the impact of production activities on the environment and comprehensively evaluate GTFP. Based on the characteristics of the research object, this article uses labor input, capital input, and energy consumption as input indicators, economic output as the expected output indicator, and industrial wastewater discharge, exhaust gas discharge, and industrial solid waste discharge as unexpected output indicators to construct an input and output indicator system to calculate GTFP (specific indicator explanations are shown in Table 1). The calculation method is as follows:

Firstly, assuming there are n decision units (DMUs), each with m inputs, s expected outputs, and q unexpected outputs. The objective function and constraints of the SBM model are shown in formula (1).

$$
\begin{aligned}
&\rho = \min \left(\frac{1+\frac{1}{q}\sum_{k=1}^{s}\frac{s_k^y}{y_{k0}}+\frac{1}{q}\sum_{l=1}^{q}\frac{s_l^b}{b_{l0}}}{1-\frac{1}{m}\sum_{i=1}^{m}\frac{s_i^z}{x_{i0}}}\right)\\
&s.t.\quad x_{i0}\sum_{j=1}^{n}\lambda_j x_{ij}+s_i^x,\quad \forall i\\
&y_{k0}\sum_{j=1}^{n}\lambda_j y_{kj}-s_k^y,\quad \forall k\\
&b_{l0}\sum_{j=1}^{n}\lambda_j b_{lj}+s_l^b,\quad \forall l\\
&s_i^x \geq 0,\quad s_k^y \geq 0,\quad s_l^b \geq 0\\
&\lambda_j \geq 0,\qquad \sum_{j=1}^{n}\lambda_j = 1
\end{aligned}
\tag{1}
$$

Table 1. Explanation of GTFP Calculation System Indicators.

Input	Labor input	Number of employed individuals in each province
	Capital investment	Actual capital stock calculated based on 2011
	Energy consumption	Total energy consumption
Expected output	Economic output	GDP
Undesirable output	Industrial wastewater discharge volume	Industrial wastewater discharge volume
	Exhaust emissions	Sulfur dioxide emissions
	Industrial solid waste discharge volume	Industrial solid waste discharge volume

Among them, x_{i0}, y_{k0} and b_{l0} represent the input, expected output, and unexpected output of the 0th DMU, respectively. s_i^x, s_k^y, and s_l^b represent the relaxation variables of input, expected output, and unexpected output, respectively, and λ_j are weights.

Secondly, further reflect its ML index. The calculation formula of the Malmquist index is (2).

$$ML_t^{t+1} = \sqrt{\left(\frac{1+D_0^t(x\prime,y\prime,b\prime;y\prime,-b\prime)}{1+D_0^t(x\prime^{t+1},y\prime^{t+1},b\prime^{t+1};y\prime^{t+1},-b\prime^{t+1})}\right)\cdot\left(\frac{1+D_0^{t+1}(x\prime,y\prime,b\prime;y\prime,-b\prime)}{1+D_0^{t+1}(x\prime^{t+1},y\prime^{t+1},b\prime^{t+1};y\prime^{t+1},-b\prime^{t+1})}\right)} \quad (2)$$

Where $D_0{}^t$ and $D_0{}^{t+1}$ represent the distance functions in the SBM direction for periods T and T+1, respectively, while x', y', b' represent the adjusted inputs, expected outputs, and unexpected outputs, respectively.

This article calculates the raw data based on 2011, and some of the results are shown in Table 2. Through calculation results, it was found that from 2013 to 2023, although some regions still experienced fluctuations in GTFP in certain years, the GTFP in most regions showed an upward trend, indicating that these regions have made positive progress in the transition to a green economy. In addition, there are differences in GTFP among different regions, with significant variations observed from 2013 to 2023. Overall, the GTFP in the eastern coastal regions (such as Beijing, Shanghai, Jiangsu, Zhejiang, Guangdong, etc.) is generally higher than that in the central and western regions (such as Inner Mongolia, Gansu, Ningxia, Xinjiang, etc.). This is because, influenced by factors such as economic development level and energy utilization efficiency, the industrial structure in the eastern region is relatively optimized, the proportion of green energy is gradually increasing, and the innovation ability of green technology is strong, resulting in a higher GTFP.

(2) Core Independent Variable

This study employs the DIF Index as its primary independent variable. As outlined in Peking University's research report on the subject, this innovative metric builds upon established academic literature and conventional inclusive finance benchmarks set by global institutions. What sets it apart is its emphasis on emerging patterns in digital financial services, along with the reliability and accessibility of relevant data.

The index evaluates DIF across three key dimensions: the reach of digital financial services, user engagement levels, and the integration of digital technology into inclusive finance [6]. Comprising 33 specific indicators, it offers a thorough assessment of the sector's progress. Backed by Ant Group's extensive dataset on DIF, the index benefits from both broad data coverage and strong credibility.

(3) Mediating Variable

This study used CEI as the mediator variable. When studying how DFI affects GTFP, current literature mainly relies on total carbon emission data, but this article believes that using CEI is more appropriate. The core of GTFP is "economic efficiency under unit resource and environmental cost", so choosing CEI can more directly measure the environmental cost paid per unit output. Furthermore, from a theoretical perspective, choosing CEI is also more reasonable. DIF can improve green capital allocation and upgrade industrial institutional effects through big data technology, thereby increasing the utilization rate of low-carbon and high-efficiency sectors, accelerating the control of CEI, and ultimately achieving the goal of improving GTFP.

(4) Control variables

This study accounts for year and province fixed effects while incorporating five key control variables related to regional economic development: economic growth level, industrial composition, fiscal decentralization, educational level, and urbanization [63-66]. Educational level is operationalized through the ratio of regular middle schools to year-end registered population, while industrial structure employs

Table 2. Partial GTPF results.

Year	Anhui	Beijing	Fujian	Gansu	Guangdong	Guangxi
2013	0.989383499	1.033342209	1.005378572	0.979837499	1.081005242	1.013515849
2014	0.977563511	1.01487942	0.98904363	0.967469549	1.057974299	0.991465311
2015	0.966725791	1.059780133	1.003094423	0.937846561	1.061249718	1.011495973
2016	1.018404444	1.107178036	1.026927168	1.030856534	1.077407918	1.037224882
2017	1.020230267	1.142638757	1.034464499	1.029271148	1.123106686	0.989459843
2018	1.038400143	1.238689375	1.020640863	1.039720411	1.09779164	1.045227832
2019	1.12523692	1.250869922	1.084408093	1.037404029	1.130085657	1.002582621
2020	1.034345822	0.99840187	0.998977331	1.150651392	1.09717953	1.009671941
2021	1.041998052	0.911391601	1.133036079	0.953685364	1.179126781	1.030522647
2022	0.997302331	1.031085107	1.15341649	1.048253175	1.07530334	1.026995388
2023	1.120503592	1.235358738	1.107253613	1.023077861	1.249735826	1.046791885

Table 3. Variable definitions and descriptions.

Type of variable	Variable name	Variable symbol	Variable declaration
Explained variable	Green TPF	gtfp	Calculate the SBM-ML index from the aspects of input, output, and unexpected output
	TFP	tfp	The DEA-Malmquist model is used to measure the regional TFP from both the input and the output aspects DIF
Explanatory variables	DFI	digi	Peking University Index, take the natural logarithm
Metavariable	Carbon emissions	cei	The ratio of total provincial carbon emissions to its gross domestic product
Controlled variable	Level of regional economic development	pgdp	Per capita GDP values
	Industrial structure	tl	Differences in labor productivity among different industries
	Degree of fiscal decentralization	Finance	Local fiscal revenue-to-expenditure ratio
	Educational level	Education	Ratio of regular middle school students to year-end registered population
	Urbanization level	Urban	Urban-to-total resident population ratio

the structural deviation method to assess the alignment between factor inputs and outputs. This approach addresses gaps in prior research by quantifying sectoral productivity disparities and clarifying how industrial transformation impacts economic mechanisms [67]. Table 3 provides the formal definitions and symbolic notation for all variables.

Model Construction

To assess DIF's effect on GTFP, the following models are developed:

$$gtfp_{i,t} = \alpha_0 + \alpha_1 digi_{i,t} + \alpha_2 \sum controls_{i,t} + \alpha_3 \sum year + \alpha_4 \sum province + \varepsilon_{i,t} \quad (4)$$

Where $gtfp_{i,t}$ represents the regional GTFP of province I in period T, $digi_{i,t}$ represents the DIF index of province I in period T, $controls_{i,t}$ represents the comprehensive impact of control variables, *year* and *province* represent the fixed effect of the year and province respectively. α_0, α_1, α_2, α_3, α_4 are the coefficient items to be estimated, and $\varepsilon_{i,t}$ represents the random error term.

Concurrently, to validate hypothesis 2, CEI is incorporated as a mediating factor in the context of model (4), and the mediation role of CEI is deeply analyzed, and the following model is constructed:

$$cei_{i,t-1} = \delta_0 + \delta\beta_1 digi_{i,t-1} + \delta_2 controls_{i,t-1} + \delta_3 \sum year + \delta_4 \sum province + \varepsilon_{i,t-1} \quad (5)$$

$$gtfp_{i,t} = \theta_0 + \theta\gamma_1 cei_{i,t-1} + \varepsilon_{i,t} \quad (6)$$

In the above two equations, $cei_{i,t-1}$ is the intermediate variable, Province I's CEI in the T-1 period, and the other variables are consistent with the above. Among them, in Equation (4), the impact of DIF on CEI is studied based on the same period.

At the same time, to ensure the logical validity of the intermediary chain digi → CEI → GTFP, this article takes lagged values for both digi and CEI to ensure the time sequence of "digi → CEI first, then CEI → GTFP". In addition, incorporating the lagged digi and CEI into the formula is also because there are often some difficult-to-observe and time-varying factors at the provincial level in China (such as current policy shocks, energy price fluctuations, sudden epidemics, etc.), which may affect both the digi and CEI of the current period and directly impact GTFP. Delaying the explanatory variables by one period is equivalent to making the values of digi and CEI earlier than these potential current shocks, thereby "stripping" unobservable confounding factors in the current period and reducing endogeneity bias. Based on this, this article also used data from the same period for mechanism analysis in the empirical process. In comparison, data lagged by one period has a greater and more stable impact. Therefore, the independent variable and mediator variable are lagged by one period.

Results and Discussion

Descriptive Statistics of Variables and Root of Unit Test

Table 4 reveals striking regional variations in the growth of DIF (digi), with figures ranging from a low of 4.479 to a high of 6.145. The average score of

Table 4. Descriptive statistics of the main variables.

Variable	Sample capacity	Mean	Standard deviation	Least value	Crest value
gtfp	330	1.039	.087	.788	1.605
tfp	330	1.222	.306	.866	2.506
digi	330	5.62	.317	4.771	6.161
Coverage	330	5.546	.382	4.479	6.145
Usage	330	5.562	.356	4.676	6.236
dig	330	5.877	.203	5.384	6.167
cei	330	-.061	.116	-.573	.551

5.62 underscores the uneven distribution across different areas, highlighting significant gaps in financial technology adoption. The standard deviations of DIF and its sub-indicators (coverage, usage, and dig) are relatively high, further highlighting the pronounced regional heterogeneity in digital inclusive finance. Although the maximum and minimum values of GTFP are relatively close, the average value is slightly above 1, indicating an overall improvement in productivity levels.

Unit root analyses were performed on the variables to prevent pseudo-regression, and all variables passed the stationarity test, confirming that the data are suitable for panel regression analysis.

Baseline Regression

Prior to the regression analysis, F-tests and Hausman tests were conducted on the relevant data. Table 5 displays the findings from the initial regression analysis. In Table 5, columns (1) and (2) represent the regression results before and after the addition of independent variables, respectively.

According to Table 5, after adding DIF, the F-test result of the benchmark regression result is 44.291, with all p-values being significant at 0, indicating that the model is well-specified. The Hausman test results showed chi-square values of 97.631. Its impact on GTFP is significant at a 5% confidence level, specifically manifested as an increase of one unit of DIF, leading to an increase of 0.205 units of GTFP.

The result shows a statistically significant relationship between DIF and GTFP, with a p-value below 5%. The estimated coefficient of 0.205 demonstrates that for every additional unit of DIF, GTFP rises by 0.205 units – a result that strongly supports our first hypothesis. A deeper analysis of these regression outcomes suggests this positive correlation stems mainly from advancements in technological innovation, which appears to be the primary mechanism through which DIF influences productivity gains.

Drawing from these insights, we contend that DIF – an advanced iteration of traditional financial inclusion tailored for the digital era – effectively lowers the barriers to information processing while bridging the knowledge gap between lenders and borrowers. This, in turn, better satisfies the funding needs of enterprises and stimulates their innovative capabilities, thereby promoting technological progress and industrial development in traditional and low-carbon industries.

Table 5. Benchmark regression results.

	(1)	(2)
	gtfp	gtfp
digi		0.205**
		(2.575)
pgdp	0.000*	0.000
	(1.954)	(0.363)
Education	1.775	1.906
	(1.127)	(1.222)
Finance	-0.014	0.122
	(-0.124)	(0.985)
tl	0.087	0.044
	(0.689)	(0.345)
lnpatent	-0.030	-0.068*
	(-0.792)	(-1.701)
Urban	0.610**	-0.334
	(1.979)	(-0.701)
_cons	0.688***	0.279
	(3.660)	(1.141)
Year and regional effects	Control	Control
F-test		44.291
Chi-square test		97.631
N	330	330
R2	0.565	0.029

Note: * * *, * *, and * are significant and positive at the 1%, 5%, and 10% levels, respectively, with the t value in parentheses, the same below.

Additionally, DIF can optimize resource allocation by directing more resources to less-developed regions, introducing new financial models and technological means, and promoting consumption upgrades, thus providing new impetus for overall production efficiency and economic development.

Mediation Effect Regression

The current study employed carbon emission as an intervening factor for the empirical examination, with detailed outcomes presented in Table 6.

From the mediation effect results in Table 6, it can be seen that there is a significant difference in the significance of DIF and CEI on GTFP.

The results of the mediation effect study reflect that DIF not only directly increases GTFP but also indirectly increases GTFP through "reducing CEI". Column (2) shows that the total effect of DIF on GTFP is 0.298 (1% significant). Combined with column (1), the coefficient of DIF on CEI is -0.221. The coefficient of CEI with a lag of one period (L.cei) on GTFP is -0.274, indicating that the increase in base period DIF can reduce the current CEI. This result will have an impact on the next period and promote the development of GTFP in the next period. Therefore, this indicates that the development of DIF will not only lead to an increase in GTFP but also a decrease in CEI, which will further lead to an increase in GTFP, thus verifying hypothesis (2).

Table 6. Results of regression with mediation variables.

	(1)	(2)
	cei	L.gtfp
digi	-0.221**	0.298***
	(2.177)	(3.351)
pgdp	-0.000	-0.000
	(-1.458)	(-0.999)
Education	-1.141	1.040
	(-0.574)	(0.708)
Finance	-0.094	0.007
	(-0.593)	(0.056)
tl	-0.523***	-0.119
	(-3.252)	(-0.933)
lnpatent	-0.114**	-0.052
	(-2.242)	(-1.413)
Urban	-0.609	-0.702
	(-1.001)	(-1.410)
L.cei		-0.274***
		(-5.747)
_cons	-0.200	0.031
	(-0.641)	(0.120)
Year and regional effects	Control	Control
N	270	270
R-Square	0.126	0.256

In summary, the overall improvement of GTFP through DIF is mainly achieved through a dual mechanism of "directly promoting technological progress" and "indirectly reducing CEI". The indirect impact mechanism specifically comes from two aspects. On the one hand, DIF can alleviate the financing constraints of green emerging technologies and project development by improving financing accessibility, expanding information efficiency, and connecting the consumer end. At the same time, it can use big data risk control and online platforms to reduce information asymmetry in green projects, promote enterprises to invest more in energy conservation and emission reduction, and increase their preference for low-carbon production methods. On the other hand, the reduction of CEI means that enterprises need to allocate more resources to high productivity and low emission sectors, continuously upgrade their processes, and increase investment in clean technology research and development in order to optimize resource allocation and strengthen the positive spillover effect of technology, which will lead to an improvement in GTFP.

At the same time, there are two major characteristics worth noting in the empirical results. Firstly, the significance of the direct effect results cannot be ignored. This result indicates that DIF has also directly boosted GTFP through other channels, such as increasing innovation investment and optimizing industrial structure. Secondly, there is a delay in the mediating effect based on CEI. This is because there are multiple time delay chains between emission reduction behavior and production efficiency improvement, influenced by various factors such as technology update cycles, market response cycles, and industry linkages. Therefore, CEI only partially plays a mediating role, and the green finance function has not yet been fully released.

Heterogeneity Test

The academic literature indicates that the effect on economic progress is heavily contingent on the varying stages of development. This research divides the sample data into three distinct economic zones: the East, the Midwest, and the West, utilizing the criteria outlined by the National Bureau of Statistics for categorization. Moreover, with the help of the China Ocean Statistical Yearbook's classification guidelines, these regions are subdivided into coastal and non-coastal areas, as detailed in Tables 7 and 8.

The data in Table 9 reveal notable regional disparities in how DIF influences economic growth. Although the eastern, central, and western regions showed positive regression coefficients of 0.496, 0.152, and 0.114, respectively, it is evident that the significance of the eastern region is stronger, and the regression results of the western region are not significant. Statistically speaking, these findings hold water – the eastern region's results are significant at the 1% threshold. The results for the middle region, although significant, only hold true at a 10% confidence level. In addition, the 0.477 coefficient

Table 7. Division standard of regional development level I.

Economic area name	Classification criteria (excluding Hong Kong, Macao, Taiwan, and Tibet)
East	Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Hainan
Middle part	Shanxi, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, Hunan
The west area	Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang

Source: http://www.stats.gov.cn/hd/cjwtjd/

Table 8. Division standard of regional development level II.

Economic area name	Classification criteria (excluding Hong Kong, Macao, Taiwan, and Tibet)
Foreland	Liaoning, Hebei, Tianjin, Shandong, Jiangsu, Shanghai, Zhejiang, Fujian, Guangdong, Guangxi, Hainan
Boo-ay	Shanxi, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, Hunan, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Inner Mongolia, Ningxia, Xinjiang, Beijing, Chongqing

Source: China Ocean Statistics Yearbook

Table 9. Results of regional heterogeneity tests.

	(1)			(2)	
	The east area	The middle area	The west area	Coastal areas	Inland areas
digi	0.496***	0.152*	0.114	0.477***	0.085
(3.210)		(1.070)	(0.738)	(3.248)	(0.881)
pgdp	-0.000	0.000***	0.000	-0.000	0.000
	(-0.941)	(2.745)	(0.156)	(-0.106)	(0.280)
Education	8.964**	0.508	-1.271	7.279**	-0.947
	(2.585)	(0.191)	(-0.623)	(2.586)	(-0.515)
Finance	0.015	0.089	0.367*	0.058	0.245*
	(0.062)	(0.547)	(1.675)	(0.251)	(1.727)
tl	-0.139	0.115	0.011	0.376	0.049
	(-0.135)	(0.524)	(0.080)	(0.721)	(0.419)
lnpatent	-0.368***	-0.041	0.040	-0.324***	-0.010
	(-3.380)	(-1.078)	(0.560)	(-3.216)	(-0.262)
Urban	-0.651	-0.995	-0.213	-0.798	0.281
	(-0.677)	(-0.847)	(-0.191)	(-0.888)	(0.483)
_cons	0.444	0.697**	0.217	0.283	0.327
	(0.668)	(2.186)	(0.511)	(0.514)	(1.155)
Year and regional effects	Control	-3.934***	Control	Control	control
N	121	88	121	121	209
R2	0.240	0.306	0.148	0.242	0.144

in coastal areas also holds at a confidence level of 1%, while in inland areas, the results lack significance.

The regional heterogeneity of the impact of digital inclusive finance on economic growth revealed in Table 9 is essentially a concentrated projection of structural mismatch between "digital finance supply capacity" and "regional absorption capacity". The results indicate that the "technology finance" dividends of DIF are not neutral diffusion but are filtered by infrastructure, industrial structure, human capital, and policy response speed. In the eastern region, the high-density coverage of 5G, industrial Internet, and mobile payment enables real-time coupling of financial data and enterprise production data. The risk control model can accurately price with high-frequency variables such as orders, logistics, tariffs, and so on. Credit delivery quickly translates into R&D investment and total factor productivity. In addition, due to its high proportion of high-end manufacturing and digital economy, enterprises have a high elasticity of capital prices. The essence of the higher regression coefficient in the eastern region is that the "finance innovation value added" chain is compressed into a short feedback loop. On the other hand, in the western region of China, although the number of base stations has doubled in recent years, "network accessibility" does not equal "service accessibility": weak signals in mountainous areas, aging smartphones, and insufficient APP adaptation have led to incomplete digital footprints, and the credit system still cannot cover most farmers. At the same time, the proportion of resource-based and primary agriculture is high, the production cycle is long, collateral is scarce, and even if funds sink, there is a lack of high-return scenarios. Therefore, it is better reflected as "smooth consumption" rather than "capital deepening", and the statistical results are not significant. The central region, on the other hand, is located in a "mezzanine" zone - with relatively complete supporting traditional industries - facing the dual pressures of fragmented orders and tightened environmental constraints. DIF can only significantly alleviate liquidity constraints in a weak form at a 10% confidence level and has not yet triggered a transition to transformation and upgrading.

Table 10 shows the heterogeneity test results for various dimensions of DIF. From the results, primary indicators such as coverage and usage of digital inclusive finance have a significant positive impact on GTFP, and the impact of coverage breadth on GTFP is significant at a 1% confidence level; on the other hand, the impact of digitalization (dig) on GTFP is significantly negative.

This indicates that the widespread adoption and low-cost nature of coverage and usage have improved the efficiency of financial services in the region, thereby having a positive impact on economic growth and driving the development of GTFP. In contrast, the level of digitization involving technological applications and innovation not only requires more time to penetrate and influence economic activities but also requires sacrificing some raw materials and human resources for production. Moreover, "excessive digitization" may lead to convenient online credit flows to real estate and consumer loans, creating a crowding-out effect on productive investment, which may result in negative impacts on GTFP in the early stages of DIF development due to its level of digitization. Based on this inference, in the subsequent development of DIF, the government should pay more attention to whether the improvement of its digital level effectively translates into the improvement of the efficiency of productive financial services.

Endogeneity Test

The regression studies of the above models are all based on a hypothesis: DIF is an exogenous variable. Therefore, to detect endogeneity biases resulting from dynamic panels, omitted variables, and reverse causality in the models' estimation process, this paper

Table 10. Results of the dimensional heterogeneity test.

	(1)	(2)	(3)
	gtfp	gtfp	gtfp
Coverage	0.210***		
	(2.815)		
Usage		0.092**	
		(2.457)	
dig			-0.038
			(-0.950)
pgdp	0.000	0.000	0.000**
	(0.266)	(1.407)	(2.245)
Education	0.556	1.650	1.029
	(0.394)	(1.158)	(0.725)
Finance	0.132	0.109	-0.005
	(1.211)	(1.007)	(-0.046)
tl	0.033	0.080	0.096
	(0.288)	(0.714)	(0.846)
lnpatent	-0.063*	-0.043	-0.018
	(-1.757)	(-1.242)	(-0.521)
Urban	-0.603	0.103	0.657**
	(-1.176)	(0.297)	(2.344)
_cons	0.436**	0.514***	0.831***
	(2.365)	(2.896)	(3.330)
Year and regional effects	Control	Control	Control
N	300	300	300
R2	0.147	0.141	0.124

Table 11. Results of the robust test.

	IV Method	Proxy Variable Approach
	(1)	(2)
digi	0.186**	0.256*
	(2.566)	(1.816)
_cons	0.186**	-3.943***
	(2.566)	(-8.435)
Year and regional effects	Control	Control
N	110	330
R2	0.4979	0.565

conducts additional endogeneity tests on the relevant data. To address this issue, this article selects the lagged independent variable as the instrumental variable to correct for endogeneity problems in the model. The results of the Anderson LM statistic and the CD-F statistic both reject the null hypothesis, indicating that the instrumental variable is identifiable and not a weak instrumental variable. The regression results are shown in Table 11.

From the results in column (1) of the table, it can be seen that after the instrumental variable test, the regression results of DIF on GTFP are still significant at a 5% confidence level, indicating that the above test results pass the endogeneity test and further confirming the robustness of the baseline regression results.

Robust Test

To further confirm that the above test results are not biased by the selection of certain variables, this article selects TPF as the replaced dependent variable and further chooses the replacement variable method to conduct robustness tests on the above results. The specific results are shown in column (2) of Table 11. According to the test results, the DIF correlation coefficient is still significantly positive, indicating the robustness of the previous conclusion.

Conclusions

This research utilizes panel data from the 2013-2023 Peking University Digital Financial Inclusion Index across China's 30 provinces by employing the DEA-Malmquist index, a two-way fixed effects model, and two-stage least squares regression. The study empirically analyzes the impact of DIF on GTFP and its underlying mechanisms. The key findings reveal three main insights: First, DIF significantly contributes to enhancing regional TFP. Secondly, CEI plays a moderating role in the impact of DIF on GTFP. Thirdly, there is significant heterogeneity in the development of China's regional economy in terms of both regional and DIF dimensions.

Drawing from these findings, the study proposes the following recommendations.

To begin with, we should promote the dual drive of innovation in DIF and data governance. Financial institutions should actively develop innovative financial products and services, lower the threshold for financial services, and improve the efficiency of financial services in order to better meet the financial needs of different regions and income groups. At the same time, the government should also guide financial institutions to improve their data governance system, perfect their data governance system and data quality control mechanism, actively participate in the evaluation of national standards for data management, strengthen the accumulation of data assets, and achieve unified management, integration, and sharing of data across the entire domain.

To further advance DIF, it's crucial to prioritize infrastructure development. The government should increase investment in DIF infrastructure, especially in rural and underdeveloped areas, by improving the coverage and depth of financial services, fully leveraging the power of digital technology, and achieving deep integration of digital finance with high-end technologies like big data, artificial intelligence, and blockchain. In addition, we should actively build a digital financial service ecosystem, encourage financial institutions to reasonably lay out the digital ecosystem scene system, and improve the accessibility and inclusiveness of financial product services.

Third, we will strengthen CEI management. To achieve this goal, the government also needs to establish a CEI testing and evaluation system and improve the CEI assessment mechanism. By establishing specialized institutions and developing scientifically reasonable evaluation standards, the detection of CEI will be presented in real-time to government departments so that relevant departments can reflect changes in CEI in the assessment mechanisms of various regions in a timely manner. Using a reward and punishment mechanism based on assessment to more effectively supervise local governments. In addition, financial institutions have also increased the development of green and low-carbon financial products and strengthened risk assessment and early warning of CEI.

Conflict of Interest

The authors declare no conflict of interest.

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