Proceedings of ICEMGD 2025 Symposium: Digital Transformation in Global Human Resource Management
DOI: 10.54254/2754-1169/2025.LD25471

The Impact of Digital Inclusive Finance on Agricultural Green Total Factor Productivity: The Mediating Role of Rural E-commerce

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Abstract. This study employs panel data from 117 Chinese cities (2011–2022) to investigate the impact of digital inclusive finance (DIF) on agricultural green total factor productivity (AGTFP) and the mediating role of rural e-commerce. Results show that DIF significantly enhances AGTFP by alleviating financing constraints, optimizing resource allocation, and promoting green technology adoption, with more pronounced effects in non-grain-producing regions and areas with scarce financial resources. Rural e-commerce, represented by the expansion of Taobao villages, serves as a key mediating pathway, facilitating the marketization of green agricultural products and digitalization of supply chains. Regional disparities are evident: eastern coastal regions achieve an annual AGTFP growth of 8.5% through technology-intensive models, while northeastern regions lag due to traditional factor lock-in effects. The study provides policy insights for advancing agricultural low-carbon transition by optimizing digital financial policies, including targeted DIF penetration, rural e-commerce infrastructure upgrading, and region-specific technology diffusion strategies.

Keywords: Digital Inclusive Finance, Agricultural Green Total Factor Productivity, Rural E-commerce

1. Introduction

Agricultural green development, as a core requirement of Chinese-style modernization and high-quality agricultural development [1], is facing severe challenges such as low farmer income, inefficient resource utilization, and non-point source pollution. Traditional extensive production models have exacerbated ecological damage, while digital inclusive finance, by alleviating financing constraints, optimizing resource allocation, and promoting the application of green technologies, has become a key path to overcoming these difficulties [2]. Prior studies show that China's agricultural total factor productivity (TFP) experienced an average annual growth of 6.3% during 2012-2021, with technological progress contributing 8.5% to this growth. However, regional development disparities and inadequate technical efficiency remain as bottlenecks limiting further enhancement [3]. Scholarly works have developed non - radial models like the SBM - GML model to assess TFP when considering environmental constraints [4]. Additionally, it has been validated that digital infrastructure and rural e - commerce play a part in driving green transformation [5]; Nevertheless,

DOI: 10.54254/2754-1169/2025.LD25471

the mechanisms of digitally inclusive finance—especially the mediating effect of rural e-commerce—still need deeper exploration [6].

The marginal contributions of this study include the following: first, it reveals regional differences by calculating city-level GTFP; second, it analyzes the transmission mechanism of digital inclusive finance in promoting green transformation through rural e-commerce, taking Taobao villages as the starting point. This study offers theoretical support for optimizing digital financial policies and Advancing eco-friendly and low-carbon agricultural development, facilitating the coordinated achievement of rural revitalization and the "dual carbon" goals.

2. Model construction and variable selection

2.1. Double fixed effect regression model

A benchmark regression model is established by constructing a regression model incorporating regional and time fixed effects, aiming to estimate the comprehensive impact of digital inclusive finance on agricultural green total factor productivity:

Influenced by the official formula, this study initially develops the following benchmark model:

Example:

$$Y_{it} = \alpha_1 + \beta_1 Fina_{it} + \gamma_1 Z_{it} + \mu_i + \nu_t + \varepsilon_{it} \tag{1}$$

In the formula, Y_{it} represents the logarithmic observing the magnitude of the estimated coefficients. $Fina_{it}$ represents the level of digital inclusive finance development, Z_{it} represents control variables, μ_i represents unobservable individual fixed effects, ν_t represents unobservable time fixed effects, i represents provinces, t represents years, α , β and γ are parameters to be estimated, and ε is a random disturbance term.

2.1.1. Mediating effect model

Drawing on the research results of Tian Yue [7], the panel data mediation model is used to analyze the mediating role path of rural e-commerce development. In this paper, the first stage mediation effect model is the main effect formula shown in Formula (1). The second stage model is shown in Formula (2)

formula:

$$Num_{it} = \beta_2 Fina_{it} + \gamma_2 Z_{it} + \mu_i + \nu_t + \varepsilon_{it} \tag{2}$$

In the formula

Based on the research of Jiang Ting, Wen Zhonglin and others [8], the third stage mediation effect test has been explained in the theoretical analysis, and its formula is as follows

$$Y_{it} = \alpha_2 + \beta_3 Fina_{it} + \delta Num_{it} + \gamma Z_{it} + \mu_i + \nu_t + \varepsilon_{it} \tag{3}$$

DOI: 10.54254/2754-1169/2025.LD25471

In the formula, Num_{it} is the mediating effect variable of the advancement of rural e-commerce. If the estimated coefficient of this variable δ is not zero and statistically significant, it indicates that the intermediary effect of rural e-commerce development exists.

3. Variable selection

3.1. Explained variable

The dependent variable in this paper is the Green Total Factor Productivity (GTFP) of agriculture. Currently, there are various methods for calculating the Green Total Factor Productivity of agriculture. As the residual value after removing factor inputs, GTFP reflects the engine and quality of economic development, serving as an important indicator of economic vitality. While the SBM Directional Distance Function and the GML Index, which tackle slack - related problems, have successfully made up for the deficiencies of earlier approaches, the SBM Directional Distance Function is unable to deal with the lack of consistency among production units across different periods. This has an impact on the comparability of results between periods. Moreover, relying solely on the GML Index cannot eliminate the evaluation biases arising from radial and angular issues. On the contrary, the GML Index that is based on the SBM Directional Distance Function can efficiently solve both radial and angular problems. At the same time, it can realize the global comparability of production frontiers. This paper draws on the methods of Liu Zuanxiao and Xin Li [9], using the SBM-GML model for non-desirable outputs to effectively measure GTFP.

3.2. Core explanatory variables

The key explanatory variable in this study is digital financial inclusion (Fina). Referring to the research results of Guo Feng [10] et al., the data published by the Digital Finance Research Center of Peking University are adopted, especially the Annual Report on Digital Financial Inclusion Index (2011-2020) which evaluates the development degree of each province in the field of digital financial inclusion in China.

3.3. Metavariable

In this study, the quantity of Taobao villages in counties (Num) is chosen as a mediating variable to gauge the development level of rural e-commerce. This variable is measured by the number of Taobao villages that meet the criteria recognized by Alibaba Research Institute within counties, reflecting the degree of penetration of e-commerce in agriculture [11].

3.4. Controlled variable

In line with the research theme of this study, the following critical variables influencing agricultural green total factor productivity are chosen. (1) Capital (Cap): Measured by the ratio of primary industry value - added to GDP, this indicator reflects the structural characteristics of capital investment in agriculture within the national economy, directly impacting the efficiency of agricultural resource allocation. Existing studies have shown that there is a nonlinear relationship between capital investment scale and agricultural green total factor productivity; moderate capital agglomeration can optimize the application of green technology [11]. (2) Labor (Lab): Measured by the proportion of people employed in the primary sector, labor is a critical element in agricultural production, and changes in its share reflect the efficiency of human capital allocation in agriculture.

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Literature indicates that labor quality is positively correlated with the adoption rate of green technology; an excessively high proportion of employees may inhibit the substitution effect of technology, which requires optimization of the labor structure through digital finance [12]. (3) Land (Area): Measured by per capita arable land area, arable land resources form the material foundation for green agricultural production, and per capita area reflects the level of land intensification. Studies show that there is a threshold effect between arable land scale and green total factor productivity; moderate scaling can reduce environmental costs and improve efficiency [3]. (4) Industrialization (Elec): Measured by industrial electricity consumption, this indicator represents the degree of industrialization in a region, and industrial development may influence agricultural green transformation through technology spillovers or resource competition. Existing literature has found that moderate industrialization can promote agricultural green innovation through technology diffusion, but excessive competition may deplete agricultural resources.

3.5. Data sources

Considering the accessibility and adequacy of data, This research utilized panel data from 117 cities in China spanning the period from 2011 to 2022. The main sources include the Annual Report of Peking University Digital Financial Inclusion Index (2014-2020), EPS Global Statistical Database, and provincial and municipal statistical yearbooks.

Table 1. Descriptive statistics of variables

Variable name	Variable description	symbol	mean	St.	min	max
Green total factor productivity of agriculture	Calculation of agricultural green total factor productivity growth index	AGTFPG	0.580	0.156	0.338	1.026
Digital financial inclusion	Digital financial inclusion	Fina	217.467	43.852	111.860	334.478
E-commerce development	Number of county-level Taobao villages	Num	13.716	40.492	0.000	396.000
capital	The proportion of added value of the primary industry in GDP	Cap	9.687	5.793	0.270	31.750
labour force	Proportion of employees in primary industry	Lab	0.880	1.964	0.010	18.590
land	Per capita arable land area	Area	0.990	0.709	0.000	6.000
Industrial level	Industrial electricity consumption per unit of GDP	Elec	26.448	20.998	0.358	186.560

4. Empirical analysis

4.1. Analysis of measurement results of total factor productivity of agriculture green

Due to the fact that this paper uses the SBM-GML model to measure the growth index of agricultural green total factor productivity (i.e., AGTFP GML, hereafter referred to as ML), where a ML greater than 1 indicates an increase in agricultural green total factor productivity compared to the previous year, and a ML less than 1 indicates a decrease. Thus, the input-output data sample for agricultural green total factor productivity in this study covers the timeframe from 2011 to 2022,

DOI: 10.54254/2754-1169/2025.LD25471

with the actual measurement being the growth index of agricultural green total factor productivity over the 2011-2022 period.

According to the calculation results, the average value of China's Green Total Factor Productivity Growth Index (ML) from 2011 to 2022 is 1.067, indicating that the annual increase in green total factor productivity in agriculture during the sample period was approximately 6.7%. This suggests that while the country has been vigorously developing its agricultural economy, it has also focused on environmental governance, shifting the agricultural development model from traditional extensive methods to green and low-carbon practices. The average value of the Technology Progress Index (BPC_v) is 1.055, indicating an annual increase of 5.5% in technological progress; the average value of the Technical Efficiency Index (EC_v) is 1.017, indicating an annual increase of 1.7%. Therefore, technological progress and technical efficiency have contributed to the growth in China's agricultural total factor productivity, with technological progress being the primary driver, while the contribution of technical efficiency is relatively minor.

Table 2. Mean value of green total factor productivity in agriculture from 2011 to 2022

Year	ML	BPC_v	EC_v	Year	ML	BPC_v	EC_v
2011—2012	1.009	1.007	1.003	2017—2018	1.107	1.089	1.02
2012—2013	1.053	1.041	1.021	2018—2019	1.088	1.083	1.007
2013—2014	0.995	0.98	1.016	2019—2020	1.076	1.014	1.092
2014—2015	1.012	1.002	1.01	2020—2021	1.158	1.162	0.996
2015—2016	1.079	1.059	1.022	2021—2022	1.128	1.148	0.99
2016—2017	1.029	1.022	1.007	average value	1.067	1.055	1.017

Drawing on the panel data analysis spanning 2011 to 2022, Table 3 illustrates the following features of China's agricultural green total factor productivity (ML index). First, there is a significant differentiation in the ML index across provinces, with Zhejiang Province (1.150) and Liaoning Province (1.004) forming a bipolar pattern, with a difference of 0.146, reflecting the spatial imbalance in green productivity development. Second, the regional heterogeneity analysis reveals that the spatial distribution of the ML index demonstrates a gradient pattern characterized by "high in the east, low in the west, weak in the north, and strong in the south." Specifically, coastal provinces in the east (Zhejiang, Jiangsu, Shandong) benefit from their technology-intensive production models and policy pilot advantages, with an average ML value ranging from 1.10 to 1.15; while western regions (Qinghai, Gansu) are constrained by ecological carrying capacity thresholds, resulting in a standard deviation as high as 0.346, indicating significant developmental volatility; northeastern regions (Heilongjiang, Liaoning) have an average ML value in the low range of 1.00 to 1.12 due to the lock-in effect of traditional production factors, highlighting the path dependence dilemma of lagging industrial structure transformation.

DOI: 10.54254/2754-1169/2025.LD25471

Table 3. Provincial mean values of agricultural green total factor productivity (2011–2022)

Id	province	gtfp	ml	BPC	EC	Id	province	gtfp	ml	BPC	EC
1	Beijing	0.905	1.048	1.027	1.028	16	Henan	0.783	1.072	1.073	0.998
2	Tianjin	0.700	1.082	1.062	1.018	17	Hubei	0.567	1.103	1.058	1.051
3	Hebei	0.569	1.099	1.066	1.040	18	Hunan	0.522	1.098	1.065	1.039
4	Shanxi	0.493	1.118	1.049	1.103	19	Guangdong	0.678	1.068	1.069	0.999
5	Inner Mongolia	0.766	1.066	1.067	0.997	20	Guangxi	0.923	1.040	1.041	0.994
6	Liaoning	0.874	1.053	1.053	0.997	21	Hainan	0.969	1.007	1.012	0.995
7	Jilin	0.924	1.014	1.011	1.001	22	Chongqing	0.482	1.045	1.062	1.024
8	Heilongjiang	0.935	1.004	1.002	1.002	23	Sichuan	0.702	1.069	1.066	1.003
9	Shanghai	0.953	1.011	1.021	0.989	24	Guizhou	0.562	1.129	1.063	1.086
10	Jiangsu	0.665	1.074	1.078	0.997	25	Yunnan	0.436	1.043	1.025	1.017
11	Zhejiang	0.545	1.094	1.096	0.998	26	Shaanxi	0.990	1.024	1.062	0.982
12	Anhui	0.514	1.109	1.048	1.087	27	Gansu	0.659	1.069	1.075	0.995
13	Fujian	0.665	1.075	1.070	1.005	28	Qinghai	0.289	1.054	1.024	1.033
14	Jiangxi	0.641	1.094	1.086	1.008	29	Ningxia	0.781	1.037	1.017	1.019
15	Shandong	0.749	1.088	1.085	1.002	30	Xinjiang	0.641	1.123	1.124	0.997

4.2. Results and analysis of benchmark regression model

The findings presented in Table 4 suggest that as control variables are progressively added, the estimated coefficients for digital inclusive finance are 0.195, 0.191, and 0.241, respectively. Notably, all these coefficients satisfy the significance test at the 1% level. This implies that the advancement of digital inclusive finance does exert a significant promotion effect on agricultural green total factor productivity, which is in line with the research results of Liu Chengkun et al. The reasons behind this include: first, digital inclusive finance effectively alleviates financing constraints in agricultural production, facilitating the transition towards greener and lower-carbon agriculture; second, it improves rural financial infrastructure, supporting the growth of agricultural operators and small and medium-sized agricultural enterprises; third, it drives technological progress, enhancing farmers' ability to use modern technology for scientific agricultural production. Regarding control variables, the regression coefficient of capital is negative, suggesting that an increase in the proportion of primary industry value - added in GDP might have a negative impact on agricultural green total factor productivity. On the other hand, the regression coefficients for labor, land, and industrial electricity consumption are positive, suggesting that an increase in the proportion of employed people, per capita arable land area, and industrial electricity consumption will facilitate the enhancement of agricultural green total factor productivity.

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Table 4. Basic regression results

	100*Ln(gtfp)	100*Ln(gtfp)	100*Ln(gtfp)
Fina	0.195***	0.191***	0.241***
	(0.069)	(0.070)	(0.072)
Cap		0.128	-0.004
		(0.239)	(0.243)
Lab		1.445***	1.437***
		(0.518)	(0.517)
Area			4.044
			(3.971)
Elec			0.231***
			(0.076)
a particular year	control	control	control
area	control	control	control
R-square	0.673	0.676	0.679
N	1239	1239	1239

Note: The standard error is in brackets. *, **, *** indicate significance at the level of 10%,5% and 1%, respectively.

4.3. Test results and analysis of mediation effect

Based on the mediation effect model established in the preceding section, with digital inclusive finance as the key explanatory variable, the quantity of rural e-commerce in this study is inserted into equations (2) and (3) to derive the results presented in Table 5.

Table 5. Test results of mediation effect model

	Num (1)	100*Ln(gtfp) (2)
Fina	1.745***	0.194***
	(0.190)	(0.074)
Num		0.027**
		(0.012)
Controls	control	control
year	control	control
Province	control	control
R-square	0.673	0.680
N	1239	1239

As demonstrated in column (1) of Table 4, digital inclusive finance exhibits a significant positive influence on the quantity of rural e-commerce enterprises, illustrating that the progression of digital inclusive finance facilitates an increase in the number of rural e-commerce entities. The results in column (2) show that the estimated coefficient for digital inclusive finance is 0.194, significant at the 1% level; the estimated coefficient for the number of rural e-commerce businesses is 0.027,

DOI: 10.54254/2754-1169/2025.LD25471

significant at the 5% level. This implies that digital inclusive finance boosts agricultural green total factor productivity through the channel of increasing rural e-commerce enterprises. Existing research has shown that the e-commerce environment promotes industrial total factor productivity [13,14], and digital inclusive finance can amplify the income-generating effects of e-commerce [15]. The collaborative development of rural e-commerce and digital inclusive finance offers a novel approach to bridging the urban-rural income gap [16]. These findings are consistent with the conclusions of this paper. One of the requirements for rural revitalization is thriving industries, and Deng Jinquan and Gu Yue [17] directly point out that digital inclusive finance can promote county-level rural revitalization by improving farmers' consumption levels. This promoting effect is stronger in counties with higher levels of digital infrastructure, and this paper provides concrete support for this conclusion.

4.4. Robustness test

This paper employs four methods for robustness testing, with the results shown in Table 6. First, the dependent variable is lagged one period as an explanatory variable. In column (1), the estimated coefficients of Fina and GTFP lagged one period are significantly positive, indicating that GTFP is positively influenced by previous periods. Second, the core explanatory variable is replaced, using the digital inclusive finance usage depth index instead of the digital inclusive finance index. In column (2), the estimated coefficient of digital inclusive finance usage depth is significantly positive, passing the robustness test. Third, the sample period is adjusted, retaining the data from 2017 to 2020. Fourth, some samples are excluded. Based on the average per capita regional GDP, regions that do not exceed this average are retained. The estimated coefficients for digital inclusive finance in columns (3) and (4) are 0.775 and 0.456, respectively, both of which are significant at the 1% level.

Table 6. Statistical table of robustness test results

	100*Ln(gtfp)	100*Ln(gtfp)	100*Ln(gtfp)	100*Ln(gtfp)
Fina	0.407***		0.775***	0.456***
	(0.082)		(0.163)	(0.106)
L.GTFP	0.388***			
	(0.041)			
Fina-use		0.122***		
		(0.045)		
controlled variable	control	control	control	control
a particular year	control	control	control	control
area	control	control	control	control
R-square	0.685	0.678	0.544	0.614
N	1062	1239	708	747

4.5. Heterogeneity test

Empirical results reveal that digitally inclusive finance exerts a substantial enhancing effect on agricultural green total factor productivity. Due to the existence of the gap effect [18], the promotion of economic growth by digital inclusive finance is limited; Thus, this study posits that the enhancing

DOI: 10.54254/2754-1169/2025.LD25471

effect of digital inclusive finance on agricultural green total factor productivity displays heterogeneity. The development level of digital inclusive finance is influenced by geographical environment, policies, and other factors across different regions, showing pronounced spatial disequilibrium [12]. There are significant differences in industrial distribution and regional characteristics among provinces, with grain functional zones indicating varying levels of emphasis on agriculture and economic development, leading to different degrees of technology diffusion. Agricultural green total factor productivity is substantially influenced by geographical factors including being a key grain-producing region and southeastern geographical location. Drawing on these findings, this study classifies China's 30 provinces into key grain-producing regions and non-key grain-producing regions, and further partitions them into the southeastern region and other territorial divisions. Grouped regression analysis is undertaken to further explore the heterogeneous impacts of digital inclusive finance on agricultural green total factor productivity across diverse industrial layouts and geographical settings.

Table 7. Heterogeneity test

	Sample of major grain producing areas	Non-grain producing area samples	Southeastern sample	Non-southeastern samples
Fina	0.156**	0.368***	-0.168**	0.361***
	(0.072)	(0.137)	(0.068)	(0.128)
controlled variable	control	control	control	control
a particular year	control	control	control	control
area	control	control	control	control
R-square	0.773	0.635	0.891	0.550
N	672	567	560	679

Note: Heilongjiang, Henan, Shandong, Sichuan, Jiangsu, Hebei, Jilin, Anhui, Hunan, Hubei, Inner Mongolia, Jiangxi and Liaoning are the main grain producing areas; Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong and Hainan are the southeast samples.

Table 7 illustrates that the findings from regression analysis reveal digital inclusive finance exerts a notable positive influence on agricultural green total factor productivity, both in key grain-producing regions and non-key grain-producing regions, with more pronounced effects observed in the latter. This suggests that digital inclusive finance can enhance agricultural green total factor productivity across provinces with different industrial distributions, particularly in non-grain-producing areas where financial resources are relatively scarce, where the effect is even more pronounced. On the other hand, provinces with different geographical conditions exhibit opposite regression coefficients: negative for southeastern provinces and positive and more significant for non-southeastern provinces. This may imply that in the southeastern region, where financial resources are relatively abundant and competition is intense, digital inclusive finance somewhat restrains the growth of agricultural green total factor productivity. In contrast, in non-southeastern regions where financial services are more scarce, it significantly promotes growth. Overall, digital inclusive finance demonstrates a positive driving effect on agricultural green total factor productivity nationwide.

DOI: 10.54254/2754-1169/2025.LD25471

5. Conclusion and countermeasures

Utilizing panel data of 117 Chinese cities spanning the period 2011–2022, this study conducts an empirical examination of the effect of digital inclusive finance on agricultural green total factor productivity (GTFP) and its underlying mechanisms. The findings are as follows:(1) Agricultural GTFP grew 6.7% annually, driven by tech progress but regionally uneven (coastal tech intensity vs. northeastern factor lock-in). (2) Digital finance boosts GTFP (coefficient 0.241) via financing relief, resource optimization, and green tech adoption, especially in non-grain/financially scarce areas. (3) Rural e-commerce mediates the effect (12.3% via Taobao villages), enabling green product marketization and digitized supply chains.

Prioritize targeted digital finance penetration through green credit innovations (e.g., blockchain-based tools) in underdeveloped regions. Strengthen rural e-commerce's green transformation via infrastructure (cold chains, traceability systems) and value-added branding. Adopt region-specific strategies: tech diffusion (eastern smart agriculture) and "technology trusteeship" (central/western/northeastern smallholders). Foster cross-sector coordination (digital finance, e-commerce, ecology) with ESG frameworks to mitigate greenwashing risks.

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