Digital inclusive finance and total factor productivity in agriculture—— Evidence from China

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Abstract. Under the strategy of rural revitalization, the development of digital inclusive finance is an effective way to alleviate the long-standing problem of "difficult and expensive financing" in the "three rural areas", and is an inherent requirement for achieving high-quality development of Chinese agriculture. Based on the panel data of Chinese provinces from 2011 to 2021, this paper adopts a three-stage SBM-DEA model to measure the total factor productivity of agriculture and analyzes the impact of digital financial inclusion on total factor productivity of agriculture. The study shows that, firstly, the development of digital inclusive finance plays a more significant role in enhancing total factor productivity in agriculture, and the depth of use plays the strongest contributing role among the sub-indicators. Second, there is heterogeneity in the effects of digital inclusive finance on agricultural total factor productivity in terms of time and geographical location. Third, the mechanism analysis shows that deepening human capital and regional innovation capacity can effectively drive the growth of agricultural total factor productivity. The research in this paper contributes to a deeper understanding of how agricultural total factor productivity is measured, and the theoretical mechanisms by which digital inclusive finance drives agricultural total factor productivity.

Keywords: Digital Inclusive Finance; Total Factor Productivity in Agriculture; Regional Innovation Capacity; Human Capital.

1. Introduction

Under the new situation of "quality agriculture" and "green agriculture", Chinese agriculture not only needs to ensure the absolute safety of national food, but also needs to move towards a sustainable development model. The core force for accelerating the high-quality development of China's agriculture lies in the improvement of total factor productivity in agriculture. On the one hand, the improvement of agricultural production efficiency promotes the growth of farmers' income and effectively reduces the gap between urban and rural income distribution (Chen et al., 2020). On the other hand, accelerating the transformation of the crude agricultural development model and improving total factor productivity in agriculture is the key to solving the food problem and protecting scarce natural resources (Baldos and Hertel,2014). However, at present, "financing is difficult and expensive" in rural areas makes farmers fall into the double dilemma of technology investment and learning, and the credit constraint problem seriously hinders the improvement of agricultural total factor productivity.

In the past few years, thanks to the application of digital technology, digital inclusive finance has flourished in line with the trend. With the great advantages of convenience, low cost and low threshold, digital inclusive finance can effectively overcome the spatial limitations of traditional financial institutions, reduce service costs and alleviate the problem of information asymmetry, thus realizing the unity of efficiency and equity.

The main methods to evaluate total factor productivity are DEA-Malmquist productivity index measurement and SFA approach.The Malmquist index method combined with DEA theory helps to provide a dynamic description of production efficiency. SFA approach adds a random disturbance term to control the influence of errors and random factors. In terms of the mechanism, digital inclusive finance is conducive to expanding agricultural mechanization inputs (Sun et al., 2022), creating conditions for factor substitution and capital deepening. At the same time, digital inclusive finance accelerates the process of agricultural land transfer by alleviating credit constraints to achieve the goals of increasing agricultural quantity, quality, and efficiency (Wang and Chen, 2022). Labor, is also the biggest beneficiary under the popularity of digital inclusive finance. Digital inclusive finance promotes the transfer of agricultural labor to the non-farm sector, and boosts the economic growth of the non-farm sector, which can promote the increase of total factor productivity in agriculture by means of spillover effects and dry secondary schools (Tang et al., 2022).

Compared with the existing studies, the contributions of this paper are in the following aspects: first, there is some innovation in the measurement of total factor productivity in agriculture, based on the SBM model considering non-expected output and the three-stage DEA modeling method to construct the three-stage SBM model of non-expected output to optimize the accuracy of measuring total factor productivity in agriculture. Second, in the analysis of the theoretical mechanism, we try to study the relationship between regional innovation capacity and the advanced human capital from the perspective of regional innovation capacity. The purpose of this paper is to enrich the theoretical analysis of digital inclusive finance and agricultural total factor productivity and to find an effective path to optimize the allocation of agricultural resources, with a view to providing reference for relevant departments when planning the development of digital inclusive finance.

2. Theoretical Analysis and Hypothesis Development

2.1 Direct impact of digital inclusive finance on total factor productivity

Digital inclusive finance directly affects total factor productivity in agriculture through financing demand stimulation, increased availability of funds and optimization of resource allocation. First, at the level of financing demand, with the help of digital technology, financial services no longer rely excessively on physical outlets and personnel inputs, which improves the availability of indirect financing and effectively alleviates financing constraints (Will and Mohammad, 2018); Second, at the level of financial accessibility, the rise of digital inclusive finance has broadened the business scope of financial services, enhanced the financial accessibility of rural residents in remote areas, and to a certain extent addressed the credit barriers to the deepening of rural human capital (Zhou et al., 2021). Third, in terms of resource allocation, digital inclusive finance breaks down information silos and facilitates efficient and accurate capital orientation to improve the efficiency of capital use (Ma and Qu, 2021).In summary, hypothesis 1 is proposed.

H1: Digital inclusive finance can significantly increase total factor productivity

2.2 Indirect impact of digital inclusive finance on total factor productivity

2.2.1 Digital inclusive finance, regional innovation capacity and total factor productivity in agriculture

Digital financial inclusion can significantly improve regional innovation capacity. Digital inclusive finance is based on the way of industrial organization change, deriving new business models and service industries, which is conducive to enriching Internet functions and optimizing resource allocation, and ultimately effectively promoting the improvement of regional innovation capacity (Zhang, 2019). In reality, certain frontier technology fields usually have a large demand for capital, and the enterprises' own funds cannot promote the projects; in addition, potential external investors are not willing to invest in the technological innovation activities of enterprises for the purpose of risk avoidance. Digital inclusive finance can not only integrate the idle funds of small-scale investors into the capital supply chain and increase the savings of the capital pool (Ren and Liu, 2021); it can also help the tail-end group of traditional finance break through the barrier of financial services and alleviate financial exclusion. Ultimately, it realizes effective docking between supply and demand and fully releases the vitality of innovation and entrepreneurship (Gomber et al., 2018).

In addition to physical factors, the core of total factor productivity is the productivity growth brought by technological progress. With the gradual increase of innovation, agricultural science and technology innovation activities have sprouted, agricultural R&D investment has continued to grow, and agricultural production capacity has gradually increased (Li and Chen, 2010). From the perspective of industrial structure, the industrial layout gradually transitions from labor-intensive to technology- and knowledge-intensive, and the optimization of efficiency allocation promotes the specialized production of society (Zhang and Ma, 2022).In summary, hypothesis 2 was proposed:

H2: Digital inclusive finance improves total factor productivity in agriculture through regional innovation capacity development

2.2.2 Digital inclusive finance, human capital and total factor productivity in agriculture

Digital inclusive finance can raise the level of human capital and stimulate a new demographic dividend. It breeds digital agricultural insurance, which will further reduce farmers' precautionary risk money and have the capital space to carry out human capital investments such as education (Tang et al., 2022). In addition, digital payments and online crowdfunding have increased the availability of educational resources in remote and backward areas (Wang et al., 2022). Financial institutions have opened education deposit and loan businesses with the help of digital inclusive finance platforms to guide local residents to save and invest for education, effectively improving local residents' financial literacy and human capital (Ma and Qu, 2021).

The improvement of rural human capital acts on total factor productivity in agriculture through efficiency improvement, resource aggregation, and technology diffusion. First, educational human capital accumulation helps to enhance the contribution of intellectual capital to agricultural production and promote efficiency improvement and technological progress. In addition, rural education development is conducive to improving farmers' technology imitation and application capabilities and promoting resource aggregation and the diffusion of agricultural technologies (Yin, 2017). In summary, hypothesis 2 was proposed:

H3: Digital inclusive financial development improves total factor productivity in agriculture through human capital

3. Methods and Data

3.1 Data

This paper analyzes the impact of the growth of digital inclusive finance on total factor productivity in agriculture, using 31 provinces and municipalities directly under the central government of China from 2011 to 2021 as the study population. The relevant data are obtained from China Statistical Yearbook, Economy Prediction System. Some of the missing value data were filled using the dual MICE method.

3.2 Variables

3.2.1 Explained variables

The main explained variable is agricultural total factor productivity (*agrp*). Information on agricultural inputs and outputs across the country is used to measure it, and the relevant assessment indicators are shown in Table 1.

Table 1. Input-output variables definition

Categories	Name	Definition
Input Indicators	Labor	Number of employed people
	Land	Sown area of food crops
	Machinery	Total power of machinery
	fertilizer	Fertilizer application
	Agricultural film	Film usage
	Water Resources	Irrigation area
Output Indicators	Expected output	Agricultural output value
	Non-expected output	Natural disaster affected area
		Pest, weed and rodent damage

The three-stage SBM model with non-expected output is considered for measuring total factor productivity in agriculture, which can effectively eliminate the interference of environmental factors and random errors and make the results more realistic and objective. The following is a brief description of the calculation steps.

Stage 1: Tone proposed the SBM model considering undesired outputs based on the SBM model proposed in 2001 and 2002 (Tone, 2002).The initial efficiency of each decision unit and the input-output slack variables are calculated using the non-expected output SBM model. The basic form of the SBM model is :

$$\rho = \min \frac{1 - \frac{1}{m}\sum_{i=1}^{m}\frac{s_i}{x_{i0}}}{1 + \frac{1}{s_1 + s_2}\left(\sum_{r=1}^{s_1}\frac{s_r^g}{y_{r0}^g} + \sum_{i=1}^{m}\frac{s_r^b}{y_{r0}^b}\right)} \tag{1}$$

$$\begin{aligned} subject\ to x_0 &= X\lambda + S^- \\ y_0^g &= Y^g\lambda - S^g \\ y_0^b &= Y^b\lambda - S^b \\ S^- \geqslant 0, S^g &\geqslant 0, S^b \geqslant 0 \end{aligned} \tag{2}$$

In equation (1), ρ is the efficiency value, m ,s_1, s_2 separately represents separately the number of inputs, desired outputs and non-desired outputs. S_i^- and X_t represents the input redundancy of the decision unit and its input variables, S_r^g and Y_r^g represents the desired output deficiency of the decision unit and the desired output variables, S_k^b and Y_k^b represents the undesired output excess of the decision unit and the undesired output variables; λ represents the weight vector.

Stage 2: Referring to existing scholars (Fried et al., 2002), build a stochastic frontier model to remove environmental factors and random noise, and do further optimization of the input-output data. First, the following SFA-like regression function is constructed.

$$\begin{aligned} s_{ij}^- &= f^i(zj;\beta_i^-) + v_{ij}^- + \mu_{ij}^- \\ s_{ij}^g &= f^i(zj;\beta_i^g) + v_{ij}^g + \mu_{ij}^g \\ s_{ij}^b &= f^i(zj;\beta_i^b) + v_{ij}^b + \mu_{ij}^b \end{aligned} \tag{3}$$

Next, environmental factors, management inefficiency and random noise are separated. The formula is as follows

$$E(\mu \mid \varepsilon) = \sigma^* \times \left[\frac{\phi\left(\lambda\frac{\varepsilon}{\sigma}\right)}{\phi\left(\frac{\lambda\varepsilon}{\sigma}\right)} + \frac{\lambda\varepsilon}{\sigma}\right] \tag{4}$$

s_{ij}^- represents the slack about the input or output indicators of the city j in year i . s_{ij}^g and s_{ij}^b separately represents the slack about the desired and non-desired output indicators of the city and province j in year i , $f^2(Z_j;\beta_i)$ refers to the effect of environmental variables on the slack, β_i is the estimated parameter of the formula $zj=[z_{1j},z_{2j},\cdots,z_{kj}]$, $j=1,2,\cdots,n$. In equation (3), $v_{ij}+\mu_{ij}$ is the composite error term.

Finally, the adjustment of input-output variables is performed. After performing the second separation operation, all the decision units will be placed in the same external environment for efficiency evaluation. In this paper, the input-output data are adjusted by using the great likelihood estimation of the unknown parameters with the following equation.

$$X_{ij}^{A}=X_{ij}+[\max(f(z_j;\beta_{ij}^{-})-f(z_j;\beta_{ij}^{-}))] \\ +[\max(v_{ij}^{-})-v_{ij}^{-}],i=1,2,\cdots,m;j=1,2,\cdots,n \tag{5}$$

$$y_{ij}^{A}=Y_{ij}^{g}+[\max(f(z_j;\beta_{ij}^{g})-f(z_j;\beta_{ij}^{g}))] \\ +[\max(v_{ij}^{g})-v_{ij}^{g}],i=1,2,\cdots,s_1;j=1,2,\cdots,n \tag{6}$$

$$y_{ij}^{bA}=Y_{ij}^{b}+[\max(f(z_j;\beta_{ij}^{b})-f(z_j;\beta_{ij}^{b}))] \\ +[\max(v_{ij}^{b})-v_{ij}^{b}],i=1,2,\cdots,s_2;j=1,2,\cdots,n \tag{7}$$

ε is the joint error term, $\sigma^*=(\sigma_\mu\sigma_v)/\sigma$, $\sigma=\sqrt{\sigma_\mu^2+\sigma_v^2}$, $\lambda=\sigma_\mu/\sigma_v$, ϕ and φ are the density-normal distribution functions of the standard normal distribution, respectively.

Stage 3: The adjusted data are applied and again combined with the non-expectation SBM model for agricultural productivity measurement.

3.2.2 Explanatory variables

The core explanatory variable in this paper is the level of digital inclusive finance (*dfin*), which is represented by the digital inclusive finance index at the provincial level. The index is jointly compiled by the Digital Finance Research Center of Peking University and Ant Financial Services Group, covering data at the provincial, municipal and county levels in China (Guo et al., 2020).

3.2.3 Control variables

In the paper, other factors that may affect total factor productivity in agriculture are included as control variables based on previous literature. Rural population density (*pnd*), expressed as the ratio of the total rural population to the regional area of the province at the end of the year. Foreign investment openness (*fdi*), measured as the ratio of FDI to GDP in the province where it is located. The degree of financial development (*fin*), measured as the ratio of the amount of loans from financial institutions to GDP. Traffic accessibility (*trans*), which is expressed as road miles dividing the total area.

3.2.4 Mechanism variables

Regional innovation capacity: In the mechanism section, we first refer to the China Regional Innovation and Entrepreneurship Index compiled by the Enterprise Big Data Research Center of Peking University (*innovation1*). In addition, in order to enhance the robustness of the conclusion, reference is made to Meng et al. (2021), which uses the regional invention patent grant as a characterization of regional innovation capacity (*innovation2*).

Human capital: first, the spatial vector entrainment method is applied to measure the degree of human capital advanced (*human1*) at the provincial level in China by referring to Liu et al. (2018). Second, another traditional method is used to measure human capital. Each level of education is discounted by a certain number of years of education, and then multiplied by the number of people with that level of education to obtain the number of years of education at the provincial level (*human2*). The years of university and above are counted as 4 years, and the years of other education levels are treated as 3 years of high school, 3 years of junior high school, and 6 years of elementary school.

Table 2. Data description

Variable	Obs	Mean	Std. Dev.	Min	Max
dfin	341	5.268	0.67	2.786	6.068
breadth	341	5.125	0.831	0.673	5.984
depth	341	5.251	0.647	1.911	6.192
*d*igitalization	341	5.553	0.679	2.026	6.136
agrp	341	0.712	0.241	0.055	1.000
pnd	341	0.445	0.330	0.018	1.517
fin	341	1.128	0.427	0.410	2.420
trans	341	44.530	40.895	1.354	222.625
fdi	341	0.065	0.232	0.007	4.239
innovation1	341	4.322	0.282	2.525	4.605
innovation2	341	8.124	1.600	3.296	11.541
human1	341	6.706	0.481	5.679	8.202
human2	341	11.172	0.212	10.632	11.562

3.3 Model

To test the effect of digital inclusive finance in driving total factor productivity in agriculture, the following benchmark model is constructed.

$$TFP_{it} = \alpha_0 + \alpha_1 dfin_{it} + \alpha_c Z_{it} + \mu_i + \delta_t + \varepsilon_{it} \tag{8}$$

In equation(8), TFP_{it} is the province's level of total factor productivity in agriculture at time i, $dfin_{it}$ is the province's level of digital financial inclusion development at time i .Z_{it} denotes control variables. μ_i , δ_t separately denotes individual fixed effects and time fixed effects; The random error term ε_{it} is used to solve the systematic heteroskedasticity problem of the model. If $\alpha_1 > 0$, indicating that digital inclusive finance is positively driving total factor productivity in agriculture.

4. Empirical results

4.1 Baseline results

Table 3 reports the impact of digital inclusion finance on total factor productivity in agriculture. In columns (1) to (5), the estimated coefficients of the core explanatory variable digital inclusion finance are significantly positive under time and individual effects, regardless of the inclusion of control variables. The slightly smaller coefficient in column (5) compared to column (1) indicates that the impact of digital inclusion finance on total factor productivity in agriculture would be overestimated if the errors in the control variables are not taken into account. For this reason, the research hypothesis that digital inclusive finance promotes total factor productivity in agriculture1 is confirmed.

Table 3. Baseline results

	(1)	(2)	(3)	(4)	(5)
dfin	0.141***	0.116***	0.116***	0.083***	0.096***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
pnd		-0.215***	-0.215***	-0.194***	-0.010
		(0.002)	(0.002)	(0.004)	(0.931)
fdi			-0.003	-0.008	-0.001
			(0.928)	(0.804)	(0.964)
fin				0.119***	0.125***
				(0.004)	(0.002)
trans					-0.003*
					(0.051)
_cons	-0.031	0.199**	0.199**	0.230**	0.198**
	(0.605)	(0.032)	(0.033)	(0.013)	(0.034)
City FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
N	341	341	341	341	341
adj. R^2	0.710	0.719	0.718	0.725	0.728

Notes: *, ** and *** respectively indicate significance at the level of 10%, 5% and 1%; words in brackets mean the p-value;

4.2 Robustness test

Two methods, indicator substitution and model substitution, are used to test the robustness of the results. In the indicator replacement robustness test, the digital inclusive finance subvariables digital inclusive finance coverage breadth (*breadth*), depth (*depth*), and digitalization (*digitalization*) are used to replace the core explanatory variable digital inclusive finance index (*dfin*). In addition, the total factor productivity in agriculture are remeasured by using stochastic frontier analysis. The specific results are shown in Table 4. Among them, columns (1) to (3) report the specific coefficients of breadth of coverage, depth of use, and degree of digitization, which are 0.069, 0.088, and 0.071, respectively, all of which are statistically significant at the 1% level, indicating that all dimensions in the digital inclusive finance index contribute to the improvement of total factor productivity in agriculture, and the robustness of the conclusion is proved. Comparing the coefficients reveals that the depth of use and the degree of digitization play a more important role in enhancing total factor productivity in agriculture. Column (4) reports the results after replacing total factor productivity in agriculture, and the coefficient of the core explanatory variable digital inclusive finance remains significantly positive, enhancing the robustness of the results.

In the model replacement robustness test, the OLS model test was chosen to find that the magnitude, sign, and significance of the coefficients of the core explanatory variables were largely consistent with the baseline regression, enhancing the robustness of the results. In addition, drawing on the ideas of Chernozhukov et al. (2022), we used a panel quantile model for robustness testing. It is found that the estimated coefficients of digital finance on total factor productivity in agriculture are all significantly positive, which again validates the research hypothesis1 and enhances the robustness of the findings.

Table 4. Indicator replacement robustness tests

	agrp			*agrp2*
	(1)	(2)	(3)	(3)
breadth	0.069***			
	(0.000)			
depth		0.088***		
		(0.000)		
digitalization			0.071***	
			(0.000)	
dfin				0.120***
				(0.000)
pnd	-0.017	-0.091	-0.133	-0.012
	(0.885)	(0.420)	(0.206)	(0.931)
fdi	-0.001	-0.003	-0.001	-0.002
	(0.981)	(0.929)	(0.977)	(0.964)
fin	0.149***	0.128***	0.166***	0.157***
	(0.000)	(0.003)	(0.000)	(0.002)
trans	-0.003*	-0.002	-0.002	-0.004*
	(0.078)	(0.137)	(0.180)	(0.051)
_cons	0.316***	0.245**	0.279***	0.248**
	(0.000)	(0.011)	(0.001)	(0.034)
City FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
N	341	341	341	341
adj. R^2	0.721	0.721	0.728	0.728

Table 5. model replacement robustness test

	OLS		Q=0.25	Q=0.5	Q=0.75	*iv_post*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
dfin	0.158***	0.130***	0.133***	0.159***	0.137***		1.069***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		(0.000)
pnd		-0.102	0.010	-0.110	-0.291**		1.521*
		(0.129)	(0.885)	(0.279)	(0.016)		(0.055)
fdi		0.090*	0.089**	0.027	0.000		0.064
		(0.082)	(0.015)	(0.568)	(1.000)		(0.489)
fin		0.008	-0.051	0.067	-0.029		-0.529
		(0.831)	(0.377)	(0.279)	(0.609)		(0.108)
trans		-0.000	-0.001	-0.001	0.001		-0.011**
		(0.480)	(0.290)	(0.393)	(0.365)		(0.045)
iv_post						1.153***	
						(0.000)	
Anderson LM							87.725***
Wald F							81.100***
_cons	-0.119	0.076	-0.057	-0.090	0.285		
	(0.221)	(0.483)	(0.686)	(0.580)	(0.179)		
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	341	341	341	341	341	341	341
adj. R^2	0.183	0.219	0.728	0.728	0.728	0.182	0.182

4.3 Endogeneity test

To alleviate the endogeneity problem caused by omitted variables and bidirectional causality. In this paper, we mainly use instrumental variables to solve the problem. Referring to existing studies (Zhao et al., 2020), this paper selects the post office density in 1997 as the second instrumental variable. It is worth noting that the post office densities are all cross-sectional data, and this paper introduces a time dummy variable for each year with the interaction term between the two as an instrumental variable, which reflects the variation of the instrumental variables in the time dimension.

Columns (6) and (7) of Table 5 show the estimation results of the instrumental variables. As can be seen, the first stage of the model shows a significant positive correlation between post office density and digital inclusion in 1997, and the coefficients of digital inclusion in the second stage are all significantly positive at the 1% level, which is consistent with the baseline estimation results. In addition, for the test of the original hypothesis of "insufficient identification of instrumental variables", the p-value of LM statistic is 0.000, which significantly rejects the original hypothesis; in the test of weak identification of instrumental variables, the Wald F-statistic is greater than the critical value at the 10% level of the Stock-Yogo weak identification test. Overall, the above tests justify the instrument variables selected in this paper and further validate the positive effect of digital inclusive finance on total factor productivity in agriculture.

4.4 Mechanism results

The traditional stepwise method of analyzing mediating effects leads to lower statistical test efficacy and thus estimation bias, Jiang (2022) proposed that the previous stepwise regression method can be discarded when conducting the analysis of mediating effects, as long as a more intuitive effect of the mediating variable on the dependent variable is theoretically presented, and then the effects of the independent and dependent variables and the independent and mediating variables are tested, which can avoid formally distinguishing between the indirect effects in This avoids formally distinguishing whether there are unexplained direct effects in addition to indirect effects. Therefore, this paper refers to the results of existing scholars, and after regression analysis of digital inclusive finance and total factor productivity in agriculture, only the regression analysis of digital inclusive finance and mediating variables is conducted.

Table 6. Mechanism results

	Innovation1	Innovation2	Human1	Human2
	(1)	(2)	(3)	(4)
dfin	0.260***	0.028***	0.070***	0.525***
	(0.000)	(0.000)	(0.000)	(0.000)
pnd	-0.568***	0.092**	-0.271***	-0.427*
	(0.000)	(0.018)	(0.000)	(0.050)
fdi	0.084**	-0.022	0.047**	0.128*
	(0.012)	(0.102)	(0.026)	(0.090)
fin	0.348***	-0.035**	0.287***	0.279***
	(0.000)	(0.016)	(0.000)	(0.001)
trans	0.003***	-0.000	0.003***	0.000
	(0.002)	(0.437)	(0.000)	(0.949)
_cons	5.073***	-11.307***	3.623***	5.221***
	(0.000)	(0.000)	(0.000)	(0.000)
City FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
N	341	341	341	330
adj. R^2	0.924	0.897	0.914	0.732

The specific regression results are shown in Table 7. Among them, columns (1) and (2) are the specific results of regional innovation capacity, and columns (3) and (4) are the regression results of human capital, respectively. Specifically, digital inclusive finance can improve regional innovation capacity. It relies on the advantage of portable sharing, which enriches and broadens the ways and channels of farmers' innovation financing and improves the availability of their innovation financing. Similarly, the effect of digital financial inclusion to improve human capital has been confirmed. Further, theoretically, the ease of digital payments effectively solves the problem of availability of educational resources. In addition, education-specific deposit and loan services offered by financial institutions can guide local residents to save and invest in education, break the backward concept and mindset of farmers, and improve financial literacy, which can also further improve the human capital status of their offspring.

4.5 Heterogeneity results

The report of the 18th National Congress in 2013 pointed out the need to "promote the extensive use of information network technology", while the report of the 19th National Congress in 2017 pointed out the need to "build a digital China and a smart society". In this paper, we set 2013 and 2017 as two time points to examine the heterogeneous effects of digital inclusive finance on total factor productivity in agriculture at different time points. The results are presented in Table 8. Columns (1) to (3) show the regression results grouped by time intervals. The coefficients of the core explanatory variables in columns (2) to (3) are 0.425 and 0.613, respectively, and both pass the significance test at the 1% level, fully confirming that digital inclusive finance has played an increasingly important role in rural areas with the support of national policies. The sample is further divided into three regions, East, West and Central, to examine the possible regional heterogeneity, and (4) to (6) are the regression results grouped by spatial regions. The coefficient of the digital inclusion index is more statistically significant in the eastern region, but the coefficient of the western region is 0.061, which shows that the western region is more sensitive to the dividends brought by digital inclusion. The reason for this difference may be related to the regional economic development potential: the western region, with its rich natural resources and unique geographical location, has better development prospects in energy industry and economic trade along the border. The widespread application of digital inclusive finance can positively awaken the "latecomer advantage" of the western region.

Table 7. Heterogeneity results

	2011-2013	2014-2017	2018-2021	East	Central	West
	(1)	(2)	(3)	(4)	(5)	(6)
dfin	0.047	0.425***	0.613**	0.207***	0.036	0.061**
	(0.126)	(0.002)	(0.037)	(0.000)	(0.327)	(0.027)
pnd	0.061	0.080	-0.379**	1.171***	-0.154	-0.440***
	(0.869)	(0.866)	(0.023)	(0.009)	(0.456)	(0.005)
fdi	2.882	0.072	0.048	0.010	-0.496	-0.953
	(0.344)	(0.947)	(0.398)	(0.781)	(0.714)	(0.308)
fin	-0.170	-0.137	0.020	0.169***	0.065	0.112*
	(0.471)	(0.337)	(0.768)	(0.009)	(0.551)	(0.063)
trans	0.001	-0.003	0.002	-0.009	-0.004	0.002
	(0.917)	(0.485)	(0.181)	(0.254)	(0.354)	(0.356)
_cons	0.330	-1.338**	-2.689	-0.654***	0.742***	0.380***
	(0.167)	(0.047)	(0.118)	(0.001)	(0.001)	(0.004)
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
N	90	120	120	121	88	121
adj. R^2	0.834	0.708	0.103	0.688	0.772	0.743

5. Conclusion

As a new industry in the financial industry, digital inclusive finance has now become an important tool for optimizing the allocation of rural resources and improving total factor productivity in agriculture. This paper empirically investigates the impact of digital inclusive finance development on total factor productivity in agriculture using 31 provinces and municipalities directly under the central government of China from 2011 to 2021 as a research sample. The results show that: digital inclusive finance development has a significant contribution to agricultural total factor productivity, with each 1% increase in the digital inclusive finance index increasing agricultural total factor productivity by about 0.14%. Among them, the promotion effect of depth of use is the strongest in the digital inclusive finance subindex. Policy support has significantly increased the positive impact of digital inclusive finance on total factor productivity in agriculture. Benefiting from the industrial development conditions and potential, digital inclusive finance has a stronger promotion effect in the eastern and western regions. Digital inclusive finance development improves agricultural total factor productivity by enhancing regional innovation capacity and promoting human capital deepening.

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