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Assessing the impact of digital financial inclusion on agricultural total factor productivity in China

RESEARCH ARTICLE

Shixian Zhai[a,b], Chao Peng[c,d]ⓘ and Yu Sheng[e]

[a]*Assistant Professor,* [c]*Professor, Administration and Management Institute, Ministry of Agriculture and Rural Affairs, 209 Huangping Road, Changping District, Beijing, 102208, China P.R.*

[b]*Associate Research Fellow,* [d]*Research Fellow, Rural Development Institute, Yan'an University, Public School North Road, Baota District, Yan'an, Shaanxi, 716000, China P.R.*

[e]*Professor, School of Advanced Agriculture Sciences, Peking University, 5 Summer Palace Road, Haidian District, Beijing, 100080, China P.R.*

Abstract

Based on panel data from the National rural fixed point survey from 2011 to 2018 and the Peking University digital financial inclusion (DFI) index data, this article uses the dynamic panel fixed effect model to analyze the effect of access to digital inclusive financing platforms on agricultural total factor productivity (TFP) and its contributing factors at the household level. The results show that DFI have a significant hysteresis positive impact on agricultural TFP and its two components, agricultural technical progress and agricultural technical efficiency change. And the usage depth of financial services has the greatest effect in three dimensions of DFI index.

Keywords: digital financial inclusion, agricultural total factor productivity, agricultural technical progress, agricultural technical efficiency
JEL code: Q12, Q14

ⓘCorresponding author: 15801698196@126.com

1. Introduction

China's economy is shifting from the output-oriented to quality-oriented development path. Improving agricultural total factor productivity (TFP) is a priority of agricultural supply-side structural reform, since it helps to increase the quality, efficiency and power of agricultural development (Cao and Birchenall, 2013). Therefore, in the critical period of China's agricultural transformation of production mode and transformation of growth power, it is of great practical significance to explore the important drivers of agricultural TFP growth in promoting agricultural transformation and upgrading and accelerating agricultural modernization. With the rapid development of digital technology, digital financial inclusion (DFI) is being formed at an accelerating pace worldwide and is gradually receiving a lot of attention from the Chinese government. In July 2017, National Financial Work Conference proposed to 'build an inclusive financial system'. In 2021, the No. 1 Central Document proposed to 'develop digital financial inclusion in rural areas' for the first time. Vigorously developing rural DFI has become an important part of supply-side structural reform and high-quality development of rural finance (Chen *et al.*, 2018).

Theoretically, the development of DFI should contribute to the improvement of agricultural TFP. The original intention of DFI is to provide access to formal financial services (fast credit supply, for instance) at an affordable cost through digital technology for all members of an economy, favoring mainly low-income groups. Therefore, DFI can gradually reallocate financial resources from wealthy urban areas to poor rural areas, improve the accessibility of useful and affordable financial products and services for rural residents in a sustainable way (Diniz *et al.* 2012; Hu *et al.* 2021), and enable farmers to better play a role of financial 'living water', so as to improve both technical efficiency and technological progress, which are two main sources of TFP growth.

On the one hand, some studies suggest that specialization among industries can increase efficiency and productivity (Smith, 1776; Bohm-Bawerk,1884); however, resource misallocation can hinder TFP growth. For example, Restuccia and Rogerson (2017) show that the dynamic effects of resource misallocation on productivity growth are significant and misallocation appears to be a substantial channel in accounting for productivity differences across countries. The rapid development of DFI could help farmers adopt modern production modes (Cao *et al.*, 2019; Peng and Xu, 2019), and promote more efficient use of land, labor, technology and capital for agricultural production based on specialization and cooperation, so as to improve the allocation efficiency of agricultural resources owing to transaction cost reduction, management skill improvement and scale upgrade (Cai, 2013; Swamy and Dharani, 2016), which may bring about the improvement of technical efficiency.

On the other hand, by alleviating the rural financial repression suffered as a result of the supply of traditional finance, DFI could make it easier for farmers to access resources related to modernized production, then promote the introduction and promotion of advanced agricultural technologies in agricultural production (Miller and Jones, 2010), which are well proven to improve agricultural TFP (Badunenko and Romero-Avila, 2013; Kou *et al.*, 2020; Lapple *et al.*, 2015), so as to accelerate the progress of agricultural technology.

There are relatively few studies that focus exclusively on the impact of DFI on agricultural TFP, especially the lack of the micro analysis at the rural household level. Some literature focuses on the effect of DFI development on TFP growth, but mainly focuses on the regional economy and non-agricultural sector. Only some of the literature has analyzed the relationship between financial development and TFP growth in agriculture, but mainly at the provincial level. Some literature finds that financial resources could encourage farmers to adopt and foster technological innovations that are well documented to improve agricultural TFP (Badunenko and Romero-Ávila, 2013; Kou *et al.*, 2020; Lapple *et al.*, 2015). And resource misallocation could hinder TFP growth (Fukao and Kwon, 2006; Luo, 2018; Restuccia and Rogerson, 2017). The existing research can be supplemented and optimized from two aspects. To begin with, some literature uses provincial level data, which is easily affected by the endogenous economic growth of DFI (e.g. Hu *et al.*, 2021). Moreover, the use of aggregate data may also conceal the heterogeneous impact of DFI on small-scale farmers. Second, a few studies have overlooked the endogeneity problem mainly caused by reverse causality (Headey *et al.*, 2010; Rada *et al.*, 2019; Rahman and Salim, 2013).

This paper aims to explore the impact of DFI on agricultural TFP and its underlying mechanism. The data in use include agricultural household level panel data of national rural fixed observation sites and the DFI index of Peking University from 2011 to 2018, measuring agricultural TFP and its decomposition terms. We start our analysis by using the regression method to measure the impact of DFI on agricultural TFP. The mechanism through which DFI on agricultural TFP is further explored uses the decomposition approach. We use the dynamic panel fixed effect model to deal with the endogeneity problem.

The paper contributes to the literature in at least three ways. First, although previous studies examine the relationship between financial factors and agricultural TFP growth, the effect of DFI has not been studied extensively (Bravo-Ortega and Lederman, 2004; Ciaian *et al.*, 2012; Spicka and Machek, 2015; Rada *et al.*, 2019). Therefore, we focus exclusively on the effect of DFI on agricultural TFP growth in China. Second, most of the existing literature uses aggregated data at the provincial level, which may not only obscure the heterogeneous effect of DFI on micro farmers but may also cause the endogeneity problem. As it is difficult for a single farmer to influence the development of regional DFI, the development of DFI in household level data is more exogenous compared with the provincial level data. We use the agricultural household level panel data of national rural fixed observation sites, which may not only alleviate the problem of endogeneity, but may also to a certain extent avoid the statistical and aggregation errors of the use of macro data measuring agriculture TFP. Third, the data used in this paper has a long time span (2011-2018), which can fully capture the changes in agricultural growth effects brought about by the development of DFI. In addition to TFP, this paper also examines the impact of DFI on agricultural technical efficiency changes and technological progress, in order to gain a deeper understanding of the impact of DFI on agricultural TFP.

The remainder of the paper is organized as follows. In Section 2, we discuss research methods and data. The empirical results are presented and analyzed in Section 3. We conclude and discuss the policy implications of our results in Section 4.

2. Research methods and data

2.1 Research methods

■ *Agricultural total factor productivity measurement*

In order to analyze the impact of DFI on farmers' agricultural TFP, we use panel fixed effect stochastic frontier analysis (SFA) and Malmquist productivity index to measure and decompose agricultural TFP. Malmquist productivity index was established by Caves *et al.* (1982) on the basis of Malmquist quantity index and Shepherd distance function to measure the change of TFP. Both parametric and non-parametric approaches can be used to measure this index (Ang and Kerstens, 2017; Fulginiti and Perrin, 1997; Gong, 2018; Hayami and Ruttan, 1970; Headey *et al.*, 2010). The commonly used parameter method mainly focuses on SFA, and the commonly used non-parametric method is data envelopment analysis (DEA). The two methods have their own advantages and disadvantages, but compared with DEA, SFA is more consistent with the essential characteristics of agricultural production because it can prevent the impact of random factors on the frontier and is less sensitive to outliers. Therefore, this paper will adopt SFA-Malmquist productivity index method to measure and to decompose agricultural TFP at household level.

According to Kumbhakar and Lovell (2003) and Greene (2005), the panel fixed effect SFA model form is as follows:

$$lnY_{it} = \beta_0 + \sum_j \beta_j lnX_{ijt} + \beta_t t + \sum_j \sum_l \beta_{jl} lnX_{ijt} \times lnX_{ilt} + \beta_{tt} t^2 + \sum_j \beta_{jt} t \times lnX_{ijt} + \alpha_i + \varepsilon_{it} - \mu_{it} \qquad (1)$$

Where *i* and *t* are farmer and period. Y_{it} is the total output value of agriculture, forestry, animal husbandry and fishery. X_{it} is the factor input, *j* and *l* represent the j_{th} and l_{th} factor input, respectively. β is the parameter to be estimated. α_i is the unobservable individual effect of farmer. ε_{it} is the random error term, assumed to follow normal distribution $\varepsilon_{it} \sim N(0,\sigma_\varepsilon^2)$. μ_{it} is the error caused by technical inefficiency, assumed to follow truncated normal distribution $\mu_{it} \sim N(\mu,\sigma_\mu^2)$. We use the time-varying model to calculate.

We select land (T_{it}), physical capital (K_{it}) and labor (L_{it}) as input indicators. The input and output variables are standardized by land input (T_{it}) in practice, i.e. $y_{it} = Y_{it}/T_{it}$, $k_{it} = K_{it}/T_{it}$, $l_{it} = L_{it}/T_{it}$, to meet the assumption of constant returns to scale (CRS) and conform to the symmetry of translog function.

Then we can obtain the following regression model by substituting the standardized input and output variables into Equation 1:

$$lny_{it} = \beta_0 + \beta_1 lnk_{it} + \beta_2 lnl_{it} + \beta_3 (lnk_{it})^2 + \beta_4 (lnl_{it})^2 + \beta_5 lnk_{it} lnl_{it} + \beta_6 tlnk_{it} + \beta_7 tlnl_{it} + \beta_8 t + \beta_9 t^2 + \alpha_i + \varepsilon_{it} - \mu_{it} \quad (2)$$

After the above model parameters are obtained, the agricultural technical efficiency changes and agricultural technological progress can be obtained by using the calculation formula of existing studies (among others Aigner *et al.*, 1977; Zhu *et al.*, 2019).

The Malmquist productivity index, used to measure the change of TFP, can be decomposed into two components, namely, technical progress index (TPI) and technical efficiency change index (TEI). The change of TFP can be expressed as follows:

$$TFP_{t,t+1} = TPI(x_t, y_t, x_{t+1}, y_{t+1}) \times TEI(x_t, y_t, x_{t+1}, y_{t+1}) \quad (3)$$

The two components TPI and TEI correspond to the two terms on the right side of Equation 3, and the increase or decrease of any component corresponds to the increase or decrease of the TFP index.

■ *Econometric models*

To estimate the impact of DFI on agricultural TFP, we establish a panel fixed effect (FE) model. The regression equation set in this paper is as follows:

$$lnY_{it} = \gamma + \theta lnDFI_{it} + \sum \sigma_i Z_{it} + \alpha_i + \vartheta_t + \varepsilon_{it} \quad (4)$$

Where Y_{it} represents the agricultural TFP and the decomposed technical progress index (TPI) and technical efficiency change index (TEI) calculated by the SFA-Malmquist index method. γ is a constant term. DFI_{it} is the DFI development level of the county (city) where the i_{th} farmer resides in t_{th} year. Z_{it} are other control variables at the household and village levels that change over time and affect the TFP of farmers. α_i and ϑ_t represent farmer individual fixed effects and year fixed effects, respectively. ε_{it} is the random error term. The coefficient θ is the core parameter in this paper.

2.2 Data

The main data of this paper comes from the agricultural household level panel data of national rural fixed observation sites from 2011 to 2018, which covers a total of 360 villages and 23,000 rural households in 31 provinces (autonomous regions and municipalities) except Hong Kong, Macao and Taiwan. The data content includes detailed information on the characteristics of rural households and their members, household production and operation, household income and expenditure, village characteristics and other aspects, which provides a good base for our research.

The variables of DFI in this paper are derived from the Peking University digital financial inclusion index of China (PKU_DFIIC). The index covers 31 provinces (and municipalities directly under the Central Government and autonomous regions), 337 cities above the prefecture level (and regions, autonomous prefectures, alliances, etc.), and nearly 2,800 counties (and county-level cities, banners, municipal districts, etc.). The data for some regions are missing, for example Hong Kong SAR, Macao SAR and Taiwan province. The time span is 2011-2020 for provincial level and prefecture level, 2014-2020 for county level.

This paper combined the farmer data of national rural fixed observation sites with the PKU_DFIIC using the county names and regionalism codes based on the codes at the end of 2014[1]. After excluding the rural households without agricultural production and those with missing values of major production variables, we obtained the data of 17,142 rural households from 2011 to 2018. Since the calculation of TFP is a dynamic efficiency evaluation, after removing the 2011 data, the final sample size of model estimation analysis is 16,417, which is an unbalanced panel data. The year and provincial distribution of samples are shown in Figure 1 and Figure 2 respectively.

2.3 Variable setting and descriptive analysis

■ *Explained variables*

The explained variables are the agricultural TFP and its decomposition of technical progress and technical efficiency changes. With regard to the selection of measuring indicators of farmers' agricultural TFP, combined with Cobb-Douglas production function and the relationship between input and output of agricultural production, we select farmers' annual aggregate income data (unit: Yuan) of single income from agriculture, forestry, animal husbandry and fishery as the output index[2]. The input indicators are generally classified into three broad categories: (1) Land input index: We select the sum of cultivated land area, garden land area, forest land area, grassland and grazing land area and water area at the end of the year (unit: Mu) as the land input index. (2) Capital input index: We select farmers' total production and operation expenses (unit: Yuan) from agriculture, forestry, animal husbandry and fishery, including the cost of seed and seedling, fertilizer, agricultural film, pesticide, water and electricity and irrigation, animal power, machinery operation, fixed

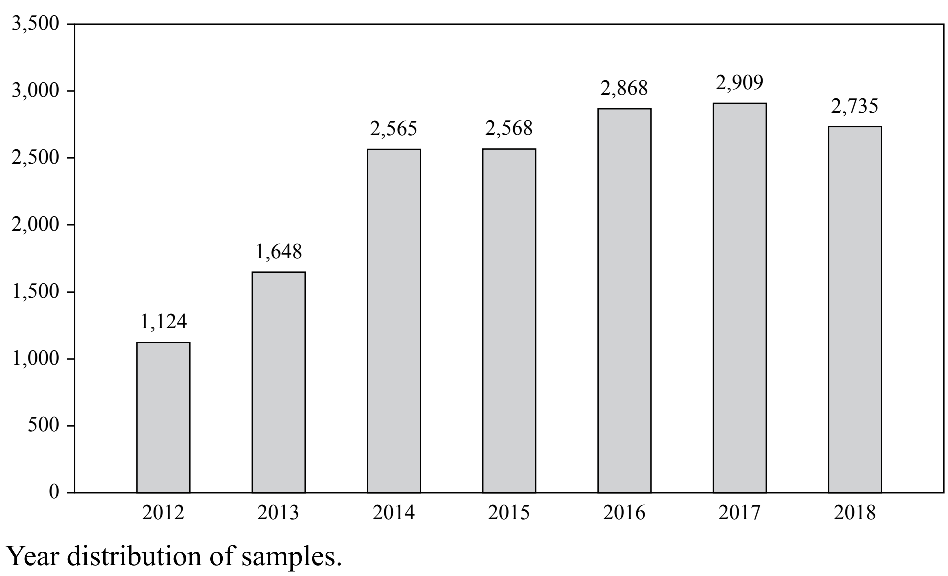

Figure 1. Year distribution of samples.

[1] During the period 2011-2020, some regions in China carried out reforms such as 'setting up cities by withdrawing regions' and 'changing counties (and county-level cities) into municipal districts', which changed the regional names and regional codes, but did not affect the statistics of this index. The codes of prefecture level cities in this index retained both versions of 2014 and 2018.We choose the 2014 version to combine national rural fixed observation sites data for further analysis.

[2] The income value is adjusted by producer price indices for farm products.

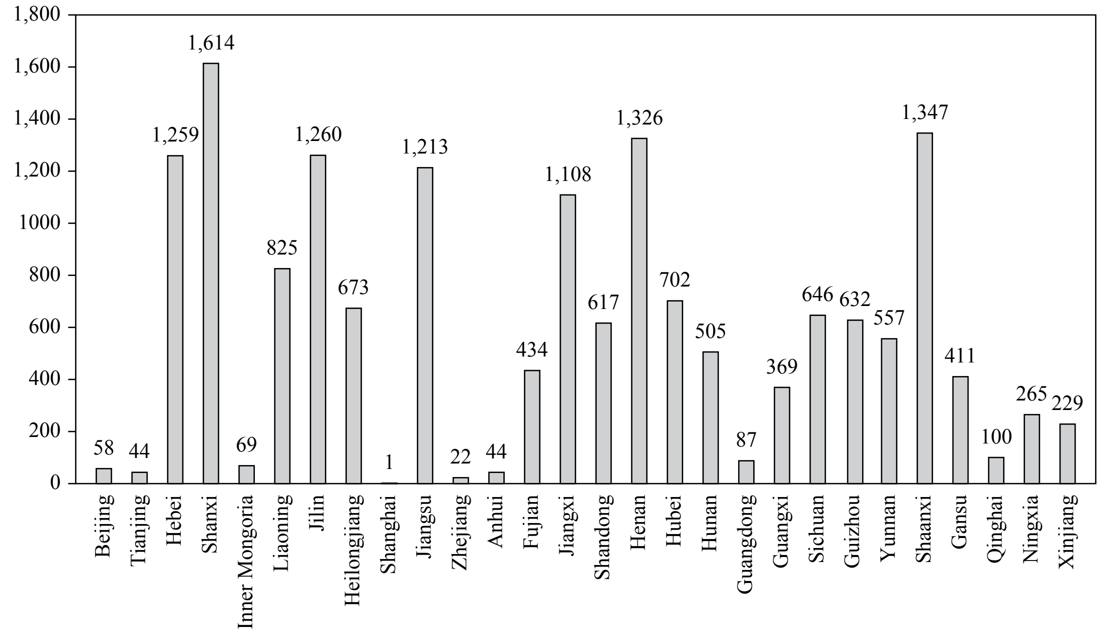

Figure 2. Provincial distribution of samples.

assets depreciation and repair, small farm tools, larder and seedling, feed, disease prevention and control, and other production and operation expenses[3]. (3) Labor input index: We select aggregate data of household employment and labor inputs (unit: Day) from agriculture, forestry, animal husbandry and fishery. The above data are used to calculate the agricultural technical efficiency, technical progress and TFP of farmers.

■ *Explanatory variables and control variables*

The explanatory variable is county-level or prefecture-level DFI index. The PKU_DFIIC uses the dimensionless method and analytic hierarchy process to calculate the score and dimensions of the DFI index, involving coverage breadth, usage depth and digitization level; usage depth involves sub-indexes such as payment, credit, insurance, credit, investment, and money funds[4]. As for the selection of control variables, we introduce three groups of control variables reflecting the individual characteristics of householders, family characteristics and village economic conditions into the model by referring to existing studies. Specifically, there are age and education level of household head, proportion of household agricultural labor force, per capita arable land area of household, logarithm of per capita income of household, distance from village to main road, logarithm of per capita income of village, etc. The definitions of the variables used in the model are presented in Table 1.

Table 2 reports the descriptive statistics of the variables involved in the model. The first three rows of Table 2 show the average levels of agricultural TFP and its components for the period from 2011to 2018. The mean of agricultural TFP is 0.975, with a standard deviation of 0.244, and the means of TPI and TEI are 0.992 and 0.983, respectively. Table 2 shows that the DFI has a mean, standard deviation, minimum and maximum of 86.704, 25.613, 12.260 and 214.799, respectively. And the means of the three dimensions are 81.026, 95.253, and 89.920, respectively. 11.8% of farmers have received agricultural technical education or training. The per capita income of household (IH) and village (IV) are adjusted using the rural consumer price index (CPI) of each province over the years (2011=100).

[3] The capital input value is adjusted by price index of agricultural means of production (AMPI).
[4] See the meaning of the value of DFI-related index for more details from Guo *et al*. (2020).

Table 1. Definitions of variables.

Abbreviations	Descriptions	Explanations
TFP	agricultural total factor productivity	TPI × TEI
TPI	technical progress index	$[(1+\partial ln y_{it}/\partial t)\times(1+\partial ln y_{it+1}/\partial(t+1))]^{1/2}$
TEI	technical efficiency change index	$TEI(x_{t+1},y_{t+1})/TEI(x_t,y_t)$
DFI	digital financial inclusion	lnDFI=natural logarithm of DFI from PKU-DFIIC
DFI_CB	coverage breadth	lnDFI_CB =natural logarithm of DFI_CB from PKU_DFIIC
DFI_UD	usage depth	lnDFI_UD =natural logarithm of DFI_UD from PKU_DFIIC
DFI_DL	digitization level	lnDFI_DL =natural logarithm of DFI_DL from PKU_DFIIC
age	age of household head	lnage=natural logarithm of age
education	education level of household head	education years
AT	agricultural technical education or training	yes=1; no=0
AL	proportion of household agricultural labor force	= % in household size
LA	per capita arable land area of household	arable land area / household size
IH	per capita income of household	lnIH=natural logarithm of household income
DT	distance from village to main road	(km)
IC	per capita income of village	lnIC=natural logarithm of village income

Table 2. Descriptive statistics per variable.

Variable	Mean	Std. Dev.	Min	Max
TFP	0.975	0.244	0.401	1.598
TPI	0.992	0.027	0.925	1.042
TEI	0.983	0.245	0.400	1.600
DFI	86.704	25.613	12.260	214.799
DFI_CB	81.026	24.281	-2.730	217.310
DFI_UD	95.253	29.845	0	204.330
DFI_DL	89.920	39.654	-75.150	321.880
age	56.312	10.559	17	96
education	6.946	2.539	0	20
AT	0.118	0.323	0	1
AL	42.783	33.747	0	100
LA	2.948	4.063	0	30
IH	13,308.830	7,186.254	2,515.930	39,981.300
DT	3.863	8.695	0	100
IC	7,679.383	2,895.735	829.840	14,990.690
Land	17.837	25.743	0.1	166.2
Capital	7,593.332	11,673.850	17.265	145,747.3
Labor	154.653	148.004	0	770

Table 3 shows the results of preliminary statistics on the correlations between the DFI and the growth of agricultural TFP and its components, TPI and TEI. We divided the samples into three equal groups according to the DFI: low, medium and high development level of DFI, respectively. The correlations in Table 3 suggest some preliminary results. First, the growth of DFI could increase the agricultural TFP of rural households. Second, the positive effect of DFI growth may work through both TPI and TEI. In particular, the TPI increased first and then decreased with the increase of DFI, showing an inverted U-shaped trend; the TEI decreased first and then increased with the increase of DFI. They all show an overall upward trend. We will verify these preliminary results in the next section.

3. Results and discussion

3.1 Calculation of agricultural TFP of farmers

Table 4 reports the SFA model estimation results. Based on this parameter estimation results, and combined with equations (among others Aigner *et al.*, 1977; Zhu *et al.*, 2019), changes in agricultural TEI, TPI and TFP of sample farmers can be obtained. In addition, the biggest criticism of the SFA model is that its conclusions

Table 3. The relationship between the DFI and the agricultural TFP, TPI, TEI of rural households.

	N	**Mean**	**Std. Dev.**
TFP			
DFI_Low	5,161	0.952	0.235
DFI_Middle	5,644	0.977	0.251
DFI_High	5,612	0.993	0.243
TPI			
DFI_Low	5,161	0.975	0.016
DFI_Middle	5,644	1.001	0.022
DFI_High	5,612	0.998	0.032
TEI			
DFI_Low	5,161	0.977	0.243
DFI_Middle	5,644	0.976	0.249
DFI_High	5,612	0.995	0.242

Table 4. Panel fixed effect SFA-Malmquist model estimation results.

lny	**Coef.**	**Std. Err.**
lnk	0.208***	0.039
lnl	0.271***	0.087
$(lnk)^2$	0.041***	0.004
$(lnl)^2$	0.046	0.030
lnklnl	-0.059***	0.002
tlnk	0.002	0.004
tlnl	0.005	0.033
t	-0.111	0.080
t^2	0.008	0.013
Sigma_u	0.393***	0.003
Sigma_v	0.000	0.000
Lambda	40,876.430***	0.003
Log Likelihood	-1,474.640	
Observation	22,040	

[1] *P*-values: <0.01***, <0.05**, <0.1*.

are highly dependent on the function setting form of the model. In order to ensure the robustness of the measurement results, we adopt the LR test to test the hypothesis of the model setting from three aspects: (1) the original hypothesis should adopt C-D function form for frontier production function; (2) the original hypothesis is that there is no technological progress; (3) the original hypothesis is that technological progress is Hicks neutral. LR statistics show that all three hypotheses are rejected, and most of the variables in the model estimation results are highly significant. This shows that the SFA model fits well and provides a good foundation for further model estimation.

3.2 Analysis of dynamic panel fixed effect model estimation results

The relationship between DFI and agricultural TFP growth may be potential endogeneity caused by reverse causality. That is, although financial support for farmers can promote agricultural TFP growth, higher agricultural TFP growth can also promote the development of DFI, as the financial products and services needs of farmers would increase with higher productivity. Therefore, we adopt the dynamic panel fixed effect model to evaluate the impact of DFI on agricultural TFP. The estimated results are shown in Table 5. The estimation results show that first-order lag DFI has significant hysteresis positive effects on agricultural TFP and its two components TPI and TEI, but the current development of DFI has a significant negative effect on agricultural TEI. We can see that the coefficients of the first-order lagged term of DFI are positive at the 1% significant level. The agricultural TFP will improve 0.084 with a 1 unit increase of L.lnDFI, which is higher than the result of Bravo-Ortega and Lederman (2004), who found that the agricultural TFP will improve 0.0013 with 1% growth of credit availability in Latin American and Caribbean countries.

According to the TFP theory, agricultural TFP measures the portion of agricultural output growth that is not explained by the input growth in agricultural production, that is, the aggregate influence of other factors except factor input in the agricultural production process, including agricultural technological progress and improvement of factor utilization efficiency, etc. But these are usually based on increased investment (Schultz, 1964). The development of DFI has improved the availability of financial and credit services in rural areas and effectively alleviated financing constraints in agricultural production. The above results indicate that, on the one hand, the development of DFI has indeed played an important role in optimizing agricultural production and improving the technical efficiency of agricultural resource allocation and organization and management. On the other hand, the development of DFI allows more financial resources to be channeled

Table 5. Dynamic panel fixed effect model estimation results.

	lnTFP		**lnTPI**		**lnTEI**	
L.Y	-0.000	(0.018)	0.729***	(0.008)	-0.004	(0.018)
lnDFI	0.003	(0.010)	0.018***	(0.000)	-0.048***	(0.010)
L.lnDFI	0.084***	(0.010)	0.002***	(0.000)	0.075***	(0.010)
lnage	0.060	(0.087)	0.006***	(0.002)	0.040	(0.087)
Education	-0.015***	(0.005)	-0.001***	(0.000)	-0.015***	(0.005)
AT	0.030	(0.019)	-0.000	(0.000)	0.029	(0.019)
AL	0.001***	(0.000)	-0.000***	(0.000)	0.001***	(0.000)
LA	-0.007	(0.006)	-0.000	(0.000)	-0.008	(0.006)
lnIH	0.098***	(0.014)	-0.000*	(0.000)	0.100***	(0.014)
DT	0.000	(0.000)	0.000***	(0.000)	0.000	(0.000)
lnIC	-0.034**	(0.015)	-0.001***	(0.000)	-0.032**	(0.015)
Constant	-1.175***	(0.361)	-0.082***	(0.007)	-0.882**	(0.362)
Chi^2	145.2		135.8		217.5	
Observations	9,426		9,426		9,426	

[1] *P*-values: <0.01***, <0.05**, <0.1*.

[2] Robust standard errors are presented in parentheses.

into agricultural production and promotes agricultural technical progress. The current development of DFI may lead to a decline in the efficiency of resource allocation because of the large input of financial resources, so the positive impact of DFI mainly shows a strong hysteresis effect. Finally, the development of DFI will have an important positive impact on agricultural TFP growth from these two aspects: the improvement of agricultural technical efficiency and agricultural technical progress. So, raising agricultural TFP is crucial to promoting rural revitalization.

In addition to the DFI variable, other control variables also have significant impacts on agricultural TFP. In the model of TPI, agricultural technical education or training (AT) has no significant effect on agricultural TFP and its components. In the sample of our paper, only 11.8% of farmers have received an agricultural technical education or training, so the impact of AT on agricultural TFP is naturally limited. The proportion of households with an agricultural labor force (AL) has a positive effect on agricultural TFP and TEI, and a negative effect on TPI. The reasons are as follows: Rural households with a higher proportion of agricultural labor force mainly depended on agricultural production and were very enthusiastic about production, thus their agricultural TFP and technical efficiency were higher. However, rural households with a higher proportion of agricultural labor force usually means lower ability to learn and innovate, which makes it difficult to reach advanced technologies, thus hindering the progress of agricultural technology. Household per capita arable land area (LA) has a non-significant restraining effect on agricultural TFP and its two components, which is corroborated by the widely argued inverse relationship between household size and productivity in developing countries (Assuncao and Ghatak, 2003; Bizimana *et al.*, 2004). Household per capita income (lnIH) plays a significant role in promoting the agricultural TFP and TEI. The distance from village to main road has a positive effect on agricultural TPI, which is consistent with the research results of Zheng and Ma (2021), who show that the effect of financial market development on the efficiency of agricultural resource allocation is affected by the relative level of local resource allocation efficiency.

3.3 Results of robustness test

An index system of DFI is usually used in related studies to measure dimensions such as the usage, availability, utility, and affordability of banking services (Beck *et al.*, 2007; Chen *et al.*, 2018; Sarma, 2016). For example, Leon and Zins (2020) use the World Bank Findex database to measure the financial inclusion level in different countries. We use the sub-indexes of DFI, including DFI_CB DFI_UD and DFI_DL, to perform robustness test. DFI_CB (coverage breadth) measures the proportion of people and regions covered by the digital financial products and service. DFI_UD (usage depth) measures the types, number and frequency of the digital financial products and services actually used. DFI_DL (digitization) measures the low cost and ease with which financial services can be implemented using digital technologies. The results in Table 6 show that the first-order lag DFI_CB DFI_UD and DFI_DL all have significant hysteresis positive effects on agricultural TFP and its two components TPI and TEI. The current development of DFI_CB (coverage breadth) has a significant negative effect on agricultural TFP and TEI, and the current development of DFI_UD (usage depth) has a significant negative effect on agricultural TEI. We can also find that DFI_UD (usage depth) has the greatest positive effect on TFP (0.086) and TEI (0.082), which means the greater the use of the types, number and frequency of the digital financial products and services, the greater the significant hysteresis positive effects of DFI on agricultural TFP and its two components TPI and TEI.

3.4 Results of heterogeneity analysis

Next, we perform a subsample analysis to take into account the heterogeneity. First, we divide the sample into three groups using the education level of household head, primary school and below, junior high school, senior high school or above. The results of the educational heterogeneity analysis are reported in Table 7. The results show that the higher the education level of the household head, the greater the significant hysteresis positive effects of DFI on agricultural TFP and its two components TPI and TEI. The coefficient of L.DFI is the highest in senior high school or above group (0.103), and lowest in the primary school and below group (0.070), both at the 1% significance level. The results indicate that the improvement of education level is conducive to better playing the promoting role of DFI.

Table 6. Estimation results of robustness test.

	lnTFP		lnTPI		lnTEI	
L.Y	-0.009	(0.018)	0.904***	(0.005)	-0.013	(0.018)
DFI_CB	-0.018**	(0.008)	0.006***	(0.000)	-0.057***	(0.008)
L.DFI_CB	0.068***	(0.009)	0.001***	(0.000)	0.057***	(0.009)
Chi^2	138.0		160.7		203.4	
Observations	9,417		9,417		9,417	
L.Y	0.003	(0.018)	0.637***	(0.011)	0.002	(0.018)
DFI_UD	0.010	(0.010)	0.020***	(0.001)	-0.040***	(0.010)
L.DFI_UD	0.086***	(0.011)	0.001***	(0.000)	0.082***	(0.011)
Chi^2	134.5		136.7		194.7	
Observations	9,419		9,419		9,419	
L.Y	-0.011	(0.018)	0.731***	(0.008)	-0.007	(0.018)
DFI_DL	0.028***	(0.009)	0.014***	(0.000)	-0.010	(0.009)
L.DFI_DL	0.068***	(0.008)	0.001***	(0.000)	0.064***	(0.007)
Chi^2	194.0		164.2		228.8	
Observations	9,404		9,404		9,404	

[1] *P*-values: <0.01***, <0.05**, <0.1*.

[2] Robust standard errors are presented in parentheses.

Table 7. Estimation results of heterogeneity analysis (education).

	lnTFP		lnTPI		lnTEI	
L.Y	-0.001	(0.027)	0.7240***	(0.011)	-0.005	(0.027)
DFI	-0.004	(0.015)	0.0180***	(0.001)	-0.055***	(0.015)
L.DFI	0.070***	(0.014)	0.0020***	(0.000)	0.062***	(0.014)
Chi^2	52.80		360.7		82.79	
Observations	4,097		4,097		4,097	
L.Y	-0.004	(0.025)	0.745***	(0.011)	-0.009	(0.025)
DFI	0.008	(0.014)	0.017***	(0.001)	-0.042***	(0.014)
L.DF	0.096***	(0.014)	0.002***	(0.000)	0.087***	(0.014)
Chi^2	93.65		236.7		127.6	
Observations	4,525		4,525		4,525	
L.Y	0.069	(0.055)	0.743***	(0.027)	0.060	(0.055)
DFL	0.020	(0.033)	0.020***	(0.002)	-0.031	(0.034)
L.DFI	0.103***	(0.032)	0.003***	(0.000)	0.094***	(0.032)
Chi^2	46.04		132.82		45.93	
Observations	804		804		804	

[1] *P*-values: <0.01***, <0.05**, <0.1*.

[2] Robust standard errors are presented in parentheses.

Second, we divide the sample into three groups using the arable land area, small-scale, middle-scale and large-scale. The results are reported in Table 8. The results show that the significant hysteresis positive effects of DFI on agricultural TFP and its two components TPI and TEI are U-shaped. The coefficient of L.DFI is the highest in the large-scale group (0.113), and lowest in the middle-scale group (0.073), both at the 1% significance level. The results indicate that the development of DFI has a greater promotion effect of TFP on large-scale farmers.

Table 8. Estimation results of heterogeneity analysis (arable land area).

	lnTFP		lnTPI		lnTEI	
L.Y	0.011	(0.025)	0.748***	(0.011)	0.004	(0.025)
DFI	-0.015	(0.014)	0.018***	(0.001)	-0.065***	(0.014)
L.DFI	0.074***	(0.014)	0.002***	(0.000)	0.065***	(0.014)
Chi^2	59.36		245.7		85.04	
Observations	4,111		4,111		4,111	
L.Y	-0.026	(0.033)	0.690***	(0.015)	-0.028	(0.033)
DFI	0.020	(0.020)	0.020***	(0.001)	-0.032	(0.020)
L.DF	0.073***	(0.019)	0.003***	(0.000)	0.064***	(0.019)
Chi^2	57.78		341.5		73.01	
Observations	2,735		2,735		2,735	
L.Y	-0.013	(0.033)	0.722***	(0.014)	-0.021	(0.033)
DFL	0.027	(0.018)	0.017***	(0.001)	-0.023	(0.018)
L.DFI	0.113***	(0.017)	0.002***	(0.000)	0.105***	(0.017)
Chi^2	100.4		476.42		120.4	
Observations	2,471		2,471		2,471	

[1] *P*-values: <0.01***, <0.05**, <0.1*.

[2] Robust standard errors are presented in parentheses.

Third, we divide the sample into three groups using the per capital income level, low-income, middle-income and high-income. The results of income heterogeneity analysis are reported in Table 9. The results show that the significant hysteresis positive effects of DFI on agricultural TFP and TEI are inverted U-shaped. And the higher the per capital income level, the greater the significant hysteresis positive effects of DFI on agricultural TPI. The results indicate that the development of DFI has a greater promotion effect of TFP on middle-income farmers.

Table 9. Estimation results of heterogeneity analysis (income).

	lnTFP		lnTPI		lnTEI	
L.Y	-0.001	(0.034)	0.751***	(0.012)	-0.005	(0.034)
DFI	-0.002	(0.018)	0.016***	(0.001)	-0.052***	(0.018)
L.DFI	0.079***	(0.016)	0.001***	(0.000)	0.072***	(0.016)
Chi^2	89.27		48.9		121.8	
Observations	2,943		2,943		2,943	
L.Y	-0.051*	(0.026)	0.737***	(0.013)	-0.057**	(0.026)
DFI	0.023	(0.016)	0.019***	(0.001)	-0.030*	(0.016)
L.DF	0.107***	(0.015)	0.002***	(0.000)	0.097***	(0.015)
Chi^2	105.5		53.9		73.01	
Observations	3,208		3,208		3,208	
L.Y	0.033	(0.028)	0.705***	(0.014)	0.026	(0.029)
DFL	0.034*	(0.021)	0.020***	(0.001)	-0.016	(0.021)
L.DFI	0.079***	(0.018)	0.003***	(0.000)	0.070***	(0.018)
Chi^2	47.14		44.5		120.4	
Observations	3,275		2,471		2,471	

[1] *P*-values: <0.01***, <0.05**, <0.1*.

[2] Robust standard errors are presented in parentheses.

4. Summary and conclusions

Using a panel data from the National rural fixed point survey from 2011 to 2018 and the Peking University DFI index data, we analyze the effect of DFI on agricultural TFP growth and its contributing factors at the household level. Dynamic panel fixed effect models were employed to address the potential endogeneity concern. The results show that the development of DFI has significant hysteresis positive effects on agricultural TFP and its two components, TPI and TEI. The agricultural TFP will improve 0.084 with 1 unit increase of L.lnDFI. And the usage depth of financial services in rural areas has the greatest effect. Our heterogeneity analysis suggests that (1) the improvement of education level is conducive to better play the promoting role of DFI; (2) the development of DFI has a greater promotion effect of TFP on large-scale farmers; (3) the development of DFI has a greater promotion effect of TFP on middle-income farmers.

The conclusions of this paper have the following policy implications. First, government and financial institutions should continue to promote DFI growth, especially the usage depth of financial products and services in agricultural production, which will effectively promote agricultural TFP growth. Second, government should increase investment in education and training in rural areas, effectively improve farmers' ability to obtain and use financial products and services, and gradually resolve the 'digital divide' caused by farmers' lack of financial ability. Third, we should promote the popularization of DFI, increase access to financial products and services by small farmers, and organically connect small farmers with the development of modern agriculture to increase agricultural production and income.

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