Impact of Digital Finance on Large-Scale Farmers' Agricultural Productivity in China

Yu Tang

College of Economics, Sichuan Agricultural University, Chengdu, Sichuan, China

2020208017@stu.sicau.edu.cn

Abstract. Based on the CLDS2018 survey data, this paper explores the impact of digital finance on large-scale farmers' agricultural productivity in China. The results indicate that digital finance can significantly improve large-scale farmers' agricultural productivity. Additionally, further researches show that digital finance has a higher increasing effect on agricultural productivity of large-scale farmers with high education levels; and it has a stronger impact on areas with higher levels of digital finance development than areas with lower levels.

Keywords: digital finance; large-scale farmers; agricultural productivity

1 Introduction

Digital finance is the use of new digital technologies such as blockchain, big data, cloud computing and artificial intelligence to empower the financial industry, change financial service models and expand traditional financial services. Digital finance effectively enhances financial inclusion [1]. With the implementation of China's rural revitalization policy, the impact of digital finance on agriculture, rural areas and farmers has attracted the attention of scholars. Research shows that digital finance has a significant positive impact on farmers' income [2], consumption upgrading [3], and narrowing the gap between urban and rural areas [4]. The agricultural production of traditional small farmers is mostly self-sufficient, and large-scale farmers have gradually become the main body of modern agriculture. Existing research lacks attention to large-scale farmers. This paper focuses on large-scale farmers to explore the impact of digital finance on agricultural productivity, enriches the research of digital finance in the field of agriculture.

2 Theoretical analysis and hypothesis

Digital finance relies on various digital technologies to improve financial inclusion, improve the availability of credit for large-scale farmers, and provide financial support for agricultural production. First, the development of big data and cloud computing enables financial institutions to quickly and accurately mine historical transactions and other information of farmers from massive amounts of information, perform credit

H. Wu et al. (Eds.): CSIEDE 2022, ACSR 103, pp. 879–884, 2022.
https://doi.org/10.2991/978-94-6463-108-1_97

scoring, effectively alleviate information asymmetry, reduce collateral requirements. Second, the development of artificial intelligence can reduce the operating costs of financial institutions. Third, blockchain promotes the development of mobile payment. Compared with traditional payment systems, blockchain payment can directly perform end-to-end payment for both parties of the transaction, without involving intermediaries, and can greatly improve speed and reduce costs. improve. Financial activities such as credit transactions can be carried out through mobile terminals, breaking through the limitations of space and time, improving financing efficiency and serving more groups. After obtaining funds, large-scale farmers can expand capital investment, such as purchasing agricultural production machinery, adopting new agricultural production technologies [5,6], and expanding the scale of agricultural operations to obtain economies of scale.

Based on the above analysis, Hypothesis 1 is proposed.

H1: The development of digital finance can help improve large-scale farmers' agricultural productivity.

3 Research design

3.1 Data Sources

First, the farmers' data used in this study come from the CLDS2018 released by Sun Yat-sen University. CLDS is a large-scale comprehensive survey, including information on urban and rural areas, individuals, family status, economic society and other aspects. Second, the data of digital finance comes from the Peking University Digital Financial Inclusion Index [7], which is compiled by Peking University and Alibaba Ant Financial Service. Since CLDS2018 investigated the economic situation of farmers in the previous year, we used the total index of digital finance in 2017 to match it. According to China's national conditions, the average operating scale of each farmer household is 0.52 ha, and 90% of the farmer households manage less than 0.67 ha of land [8]. We define farmers with an operating scale of more than 0.67ha as large-scale farmers. According to research needs, we retained the large-scale farmers in rural communities, eliminated missing values and outliers, and finally retained 929 valid samples.

3.2 Variables

The Dependent variable: Agricultural productivity (agrpro) is defined as the productivity of agricultural land, expressed as agricultural income per 0.067ha of land. The logarithmic transformation is performed to fit skewed data distributions into a normal distribution.

The Core Independent Variable: This paper used the total index of digital finance at the city level to match the CLDS2018.

The Control variables: Characteristics of the individual include gender (gend), age (age), years of education (education), health status(health) of household decision-makers. Characteristics of the household include the number of members (size), the number of Party members (status), farming mode(mode), agricultural capital investment(input).

Characteristics of the village include the natural logarithm of the distance from the village to the county center (dis), whether the village has a non-agricultural industry (nonagr). Characteristics of the city include the logarithm of the gross domestic product of each city (gdp).

3.3 Method

To explore the impact of digital finance on large-scale farmers' agricultural productivity and test Hypothesis1. we established the following model:

$$agrpro_i = \alpha_0 + \alpha_1 digital_i + \alpha_2 x_i + \varepsilon_i \tag{1}$$

Where $agrpro_i$ represents the farmer i's agricultural productivity; $digital_i$ represents the development level of digital finance; x_i is a set of control variables, and ε_i is the random error term of the model.

4 Empirical results

4.1 Results of the Baseline Model

Table 1 displays the estimated results, which show that the development of digital finance has a positive impact on agricultural productivity at the 1% significance level. We claim that Hypothesis 1 is confirmed. Digital finance does improve agricultural productivity.

From the results of the control variables. Agricultural capital investment, mechanized farming, the age and health status of household decision makers have a significant effect on agricultural productivity. This is because with the increase of age, farmers have more experience in agricultural production. And the better the health of the farmer, the more time available for agricultural labor. In contrast, the number of household party members, the city's GDP, and the distance from the village to the county center significantly negatively impact agricultural productivity. Maybe the higher the level of urban economic development, more non-agricultural employment opportunities will be provided for farmers. The farther the village is from the county center, it is not conducive to the acquisition of production materials or production services, resulting in low agricultural productivity.

Table 1. Estimated results of digital finance on the agricultural productivity

	Agricultural productivity
dig	0.0140***(0.0036)
Age	0.01140***(0.0037)
Gend	0.1031(0.1786)
Education	-0.0139(0.0120)
Health	0.0876**(0.0349)
Size	0.0034(0.0160)
Status	-0.1445*(0.0752)
Mode	0.2537***(0.0882)

Input	0.3419***(0.0276)
Dis	-0.0082***(0.0017)
Nonagr	0.0112(0.1081)
Gdp	-0.1091*(0.0586)
Constant	1.2693*(0.7034)
N	929
Adj.R^2	0.2416

Standard errors are in parenthesis. ***p < 0.01, **p < 0.05, *p < 0.1

4.2 Endogenous Problems

In order to solve endogeneity problems, we referred to the research of Cao et al [9], this study adopted the internet penetration rate as an instrumental variable for digital finance. As is shown in Table 2, from the first-stage estimation results, we can see that there is a significant correlation between instrumental variables and independent variables. And the Cragg–Wald F statistic value is 201.79 more than 16.38, which indicates that there is no problem with weak instrumental variables. The second-stage regression results in the IV regression were consistent with those results of the benchmark regression, indicating the previous conclusions are robust.

Table 2. Estimated results of IV-2SLS

	The first stage	The second stage
	Digital Finance	Agricultural productivity
IV	0.5844***(0.0332)	
Digital finance		0.02252***(0.0089)
Control variables	yes	yes
Cragg-Wald F statistic		201.790
10% max IV size		16.38
Observations	929	929

Standard errors are in parenthesis. ***p < 0.01, **p < 0.05, *p < 0.1

4.3 Robustness check

In order to ensure the reliability of the regression results. First, this paper replaced the explanatory variable with one-period-lagged explanatory variable, namely, the index of digital finance in 2016. Second, from the agricultural workforce and agricultural land perspective, whether the farmers receiving skill training and the landform features of the village where the farmer located are added into regression. The results in Table 3 confirming the robustness of the benchmark results.

Table 3. Estimated results of robustness tests

	one-period-lagged index	Skill training	Landform
dig	0.0110*** (0.0034)	0.0100*** (0.0036)	0.0139***(0.0035)
Control variables	Yes	Yes	Yes
N	929	929	929
Adj.R^2	0.2369	0.2602	0.2519

Standard errors are in parenthesis. ***p < 0.01, **p < 0.05, *p < 0.1

4.4 Heterogeneity

First, we selected the average digital financial index of each city in the country as the standard to divide the cities into two groups. It can be seen from Table 4 that the simulative effect on agricultural productivity is higher in the region with a higher level of digital finance. Second, we selected the average years of education of the family decision makers in the sample as the standard to divide the samples into two groups. As shown in Table 4, digital finance has a stronger impact on agricultural productivity for large-scale farmers with higher education years. The higher the level of education, the more favorable the large-scale farmers are to adopt new agricultural production techniques, thus affecting agricultural productivity.

Table 4. Estimated results of different regions and education levels

	Regions with a high degree of digital finance development	Regions with a low degree of digital finance development	High educational level	Low educational level
dig	0.0231***(0.0055)	0.0257*** (0.0094)	0.0135*** (0.0050)	0.0127*** (0.0053)
Control variables	Yes	Yes	Yes	Yes
N	616	313	489	440
Adj.R^2	0.2420	0.2877	0.2462	0.2623

Standard errors are in parenthesis. ***p < 0.01, **p < 0.05, *p < 0.1

5 Conclusion and discussion

According to the empirical results: (1) digital finance promotes large-scale farmers' agricultural productivity significantly; and (2) analysis of heterogeneity results showed that the effect of digital finance on agricultural productivity is stronger in regions with higher levels of digital finance development; digital finance has a more significant positive impact on the agricultural productivity for large-scale farmers with higher levels of education. This study has several policy implications. First, strengthen the construction of digital financial infrastructure, increase the coverage of mobile payment in rural areas, break the digital divide, and allow all regions to share the digital dividend. Second, increase investment in education in rural areas, improve the education level of farmers, and provide targeted skills training for farmers.

References

1. Ozili, P. K. (2018). Impact of digital finance on financial inclusion and stability. *Borsa Istanbul Review*, *18*(4), 329-340.
2. Chen, B., & Zhao, C. (2021). Poverty reduction in rural China: Does the digital finance matter?. *Plos one*, *16*(12), e0261214.
3. Li, J., Wu, Y., & Xiao, J. J. (2020). The impact of digital finance on household consumption: Evidence from China. *Economic Modelling*, *86*, 317-326.
4. Yu, N., & Wang, Y. (2021). Can digital inclusive finance narrow the Chinese urban–rural income gap? The perspective of the regional urban–rural income structure. *Sustainability*, *13*(11), 6427.
5. Zhao, P., Zhang, W., Cai, W., & Liu, T. (2022). The impact of digital finance use on sustainable agricultural practices adoption among smallholder farmers: an evidence from rural China. *Environmental Science and Pollution Research*, *29*(26), 39281-39294.
6. Zhou, Z., Zhang, Y., & Yan, Z. (2022). Will Digital Financial Inclusion Increase Chinese Farmers' Willingness to Adopt Agricultural Technology?. *Agriculture*, *12*(10), 1514.
7. Guo, F.; Wang, J.Y .; Wang, F.; Kong, T.; Zhang, X.; Cheng, Z.Y(2020) . Measuring China's digital financial inclusion: Index compilation and spatial characteristics. China Econ. Q. 19, 1401–1418.
8. MARAC (Ministry of Agriculture and Rural Affairs of China)., 2019. 〈http://www.whb.cn/zhuzhan/jjl/20190301/245202.html.
9. Cao, S., Nie, L., Sun, H., Sun, W., & Taghizadeh-Hesary, F. (2021). Digital finance, green technological innovation and energy-environmental performance: Evidence from China's regional economies. *Journal of Cleaner Production*, *327*, 129458.