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Does Digital Finance Increase Relatively Large-Scale Farmers' Agricultural Income through the Allocation of Production Factors? Evidence from China

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Abstract: The inclusiveness of digital finance brings new opportunities for the development of agriculture, rural areas, and farmers. The purpose of this paper is to clarify how digital finance influences relatively large-scale farmers' agricultural income. Based on survey data from rural China, this paper systematically investigates the impact of digital finance on relatively large-scale farmers' agricultural income using the Multiple Intermediary Effect Model. The findings of this study reveal that digital finance has a substantial positive influence on relatively large-scale farmers' agricultural income, and this effect still exists after considering endogeneity and a series of robustness tests. Further mechanism analyses suggest that agricultural capital, agricultural land, and agricultural workforce play a partial mediating role between digital finance and agricultural income. The development of digital finance has a positive impact on improving agricultural capital investment and land transfer, while it has a negative impact on agricultural workforce. Moreover, the results of the grouping estimation show that digital finance has more significant effects on agricultural income for economic crops and farmers who received agricultural skills training and agricultural services. These results provide a micro explanation to promote relatively large-scale farmers' agricultural income with the accelerated popularization of digital finance, urgently needed for most emerging countries seeking high-quality rural development.

Keywords: digital finance; relatively large-scale farmers; agricultural income; agricultural capital; agricultural workforce; agricultural land rent-in; China

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1. Introduction

The development of agriculture is moving in the direction of scale, modernization, and industrialization. With the traditional small-scale and loose management farmers gradually turning to the new agricultural operation system, large-scale farmers are becoming an important subject of modern agricultural development. Promoting the income of large-scale farmers is conducive to the development of agricultural modernization and realizing rural revitalization. There are differences between the income structure of large-scale farmers and traditional small farmers. Small farmers mostly operate part-time, while large-scale farmers mostly take agricultural income as the main source of income [1], and it is necessary to pay attention to agricultural income to realize the income increase of large-scale farmers.

Agricultural credit significantly impacts the development of agriculture. Compared to the smallholders, the relatively large-scale farmers often need more funds for agricultural production. However, due to asymmetric information, high transaction costs, and lack of adequate collateral [2,3], there exist long-term threshold effects, financial exclusion, "mission drift," and "elite capture" in the rural financial market [4–6]. The development of inclusive finance has alleviated the above dilemma [7]. Many studies have found that inclusive rural finance significantly affects agriculture production, farmers' income, and welfare and can improve income inequality among farmers [8–11].

Digital finance is a product of the deep integration of traditional finance and Internet information technology, and it is a new business model in which traditional financial institutions and internet companies use digital technology to realize financing, payment, and investment [12]. One World Bank report shows that the application of digital technology has opened up new opportunities for rural areas through financial services [13]. Digital finance makes up for the shortcomings of traditional finance and is regarded as a low-cost and convenient financial service access for farmers [14]. China's financial industry has fully entered the digital finance era [15]. Digital finance breaks geographical restrictions to improve lending convenience [16,17]. Digital finance improves financial inclusion and stability [18], changes the traditional financial sector, promotes the quality and diversity of banking services [19], increases the efficiency of the financial market [20], and expands credit boundaries [21] by reducing information collection costs and transaction costs. Regarding the impact on the economy and society, digital finance helps improve residents' income, reduce the poverty rate, reduce income inequality, and narrow the urban–rural gap [22–24]. Researchers thought that digital finance can affordably improve financial services accession for rural households without access to financial services and can be regarded as a powerful tool to achieve inclusive finance [18,25–27].

The existing literature concerning the impact of digital finance on agriculture remains in its infancy, and conclusions conflict; currently, according to the 2017 China rural Internet application report, the promotion effect on agricultural production remains limited overall with rapid internalization in China's rural areas. Liu et al. also believed that inclusive digital finance significantly affects the efficiency of non-agricultural economic activities rather than agricultural production; it can significantly encourage rural households to reduce agricultural production [28]. However, Zhao et al. found that digital finance alleviates their credit constraints, which may exert an impact on the adoption of sustainable agriculture practices [29]. Sustainable agriculture is conducive to increasing agricultural productivity and income [30]. Thus, digital finance's impact on agricultural income and its mechanism is worth exploring. Digital finance has developed rapidly in China and has become an essential part of China's financial system. In a short period of more than ten years, with payment as the core, China has taken the lead on a global scale scope for digital finance development. Based on the "Digital Finance Index" released by the research group of the Digital Finance Research Center of Peking University, each province's average digital financial inclusion index has risen at rapid growth, from 40 to 341.22, during the period between 2011 and 2020. The number of Internet users in the rural area of China reached 2.84 hundred million. The data released by the China Internet Network Information Center(CNNIC) shows the 5G service coverage rate of administrative villages has reached 80% by the end of 2021. Nearly all rural residents have access to relatively stable, high-speed mobile network services. Thus, China is a compelling setting to explore this issue in-depth.

The improvement of agricultural performance results from rationalization and advancing efficiency in agriculture production factor allocation [31,32]. To the best of our knowledge, digital finance is conducive to collect information about agricultural production processes, address information asymmetries, and provide farmers with free and faster access to credit. Purchasing medical, pension, and agricultural insurance online helps to protect the physical and mental health, enhance the ability to resist risk, improve labor productivity, and increase farmers' labor supply. Digital finance is beneficial to improving financial literacy, which can promote agricultural land rent-in. The above analysis appears to change the constraints of initial agricultural production factors' endowment, further affecting the agricultural production decisions of farmers. Is this judgment accurate? If so, how? Thus, based on the logic of "digital finance-factor allocation-agricultural income", we bring agricultural capital, agricultural land transfer, and agricultural workforce supply into a unified analysis framework. This study elucidates the mechanism of allocation of production factors through which digital finance affects agriculture income from theoretical and empirical perspectives based on the China Labor Force Dynamics Survey (CLDS) 2016 and 2018. Our analysis enriches the literature in four distinct ways. First, although the relatively large-scale farmers cannot represent the general situation in China, large differences in production and operation between the relatively large-scale farmers and small-scale farmers exist. The share of relatively large-scale farmers is increasing greatly, that is, this group cannot be ignored indeed. This paper focuses on the relatively large-scale farmer. Second, we empirically test that digital finance is essential to improving large-scale farmers' agricultural income. Third, does digital finance impact agricultural income through the allocation of agricultural production factors? For agricultural capital, agricultural workforce, and agricultural land, which production factor plays the stronger mediating role? Last, we contribute to understanding the different impacts of digital finance on agricultural income by highlighting the following aspects: agricultural service, agricultural technical skills training, and crop type. We extend the extant understanding of how digital finance promotes agricultural income.

2. Literature Review and Hypothesis

2.1. Digital Finance, Agriculture, and Agricultural Income

Relying on emerging technologies, such as cloud computing, big data, and block chain [33], digitalization transforms the traditional financial system and spawns new Internet-based financial formats. Digital finance is rooted in widespread financial exclusion and is regarded to have the ability to compensate for traditional financial institutions' disadvantages [34,35]. Scholars performed theoretical exploration in conjunction with e-commerce [36]. They explored the effect of digital finance on new types of agricultural production operation entities [37], agricultural industry chains [38], and P2P online lending [39]. Specifically, the role of digital finance on agricultural income is reflected in the following three aspects:

First, digital finance improves access to credit for large-scale farmers who lacked collateral [40]. Finance improves agricultural production efficiency [41,42]. Large-scale farmers with loans will actively participate in agricultural production and benefit from doing so. Second, digital finance promotes technology innovation [43,44]. New technologies improve agricultural efficiency and output [45]. Modern agriculture depends on continuously increasing efficiency instead of relying on an unlimited expansion of productive factors [46]. Farmers will benefit from adopting new agricultural technology to improve agricultural efficiency. Third, digital finance helps the sales of agricultural products by promoting the development of e-commerce and then affects agricultural income [47]. Based on the "Metcalf law" and "long-tail theory" [48], mobile payment can more accurately match agricultural products with the needs of consumers and develop a broader market. The outbreak of COVID-19 has prompted more consumers to purchase agricultural products online in China [49]. According to the China Agricultural E-Commerce Development Report in 2022, major e-commerce platforms for agricultural products are Alibaba, JD, Meituan, Pinduoduo, TikTok, etc. Digital credit will support relatively large-scale farmers participating in agricultural products e-commerce, remove the geographical restrictions, widen agricultural product sales channels and markets, and increase agricultural income.

Based on the above analysis, we state the Hypothesis 1:

H1. *The development of digital finance can promote relatively large-scale farmers' agricultural income*.

2.2. The Mediating Role of Agricultural Capital, Agricultural Workforce, and Agricultural Land

Digital finance has substantial resource availability and more efficient resource allocation [21,34]. As shown in the above analysis, digital finance influences agricultural capital, agricultural production, and sales of agricultural products. Compared to traditional small-scale farmers, relatively large-scale farmers have comparative advantages in agricultural production; after obtaining financial support, relatively large-scale farmers are more inclined to invest in agricultural production and change the endowment of agricultural production factors. Due to the differences in the nature of agricultural production factors and their substitutability, the direction and degree of digital finance impacting various agricultural production factors are different. Therefore, we analyze them separately to pave the way for exploring how digital finance impacts agricultural income through the allocation of factors:

In terms of agricultural capital, digital finance helps to develop new technologies and apply new tools, which improve agricultural efficiency and output [45]. In correspondence, farmers' enthusiasm and expected return for agricultural production are greater. Easy accession to credit prompts farmers to invest more in the agricultural field [47]. Especially, mobile payment reduces the transaction cost of agricultural products and expands sales [47], prompting farmers to hire more labor and invest more in farm machinery, pesticides, and fertilizer [50]. Using machinery could increase farmers' income [51]. Additionally, farmers can easily purchase agricultural insurance online. Agricultural insurance is conducive to increasing farmers' input of agricultural production factors [52].

In terms of the agricultural workforce. The development of digital finance has led to economic growth, created more job opportunities, and raised the employment rate and income level of residents [53]. Manyika and other scholars have predicted that the application of digital finance will make a great contribution to the annual GDP growth of emerging economies, and that 95 million jobs will be created by 2025 [34]. Moreover, digital financial can relieve the constraints of insufficient academic education on farmers' entrepreneurial choices and partially replace the tacit knowledge of rural residents, which ultimately enhances the entrepreneurial behavior choices of the farmers [54]. In turn, these returning laborers who start their businesses promote the endogenous development of the local economy, resulting in more non-agricultural jobs.

In terms of agricultural land, the essence of agricultural land transfer is a contractual agreement between the transferee and the transferee. However, the information on the land transfer in rural areas is not smooth, which reduces farmers' willingness to rent in land, increases the transaction cost, and restricts the improvement of the agricultural land transfer system. Digital finance can obtain customer information and credit records more efficiently and accurately through the interaction of big data and digital platforms [33], alleviate the information imbalance between land supplier and demander and get rid of the "free rent" and "acquaintance society" restrictions on rural areas, disseminate financial knowledge, and improve financial literacy, which can promote large-scale farmers to rent the land [55]. Meanwhile, it is more convenient for relatively large-scale farmers to buy agriculture insurance online. Agricultural insurance encourages farmers to consolidate idle, scattered, and abandoned land and put them back into agricultural production [56]. Efficient land transfer can realize the concentration of agricultural land and obtain economies of scale, which is conducive to using advanced technologies and agricultural machinery. By renting-in agricultural land, farmers achieve large-scale operation and greater production efficiency, which has a significant impact on farmers' income [57].

Therefore, we propose the following hypothesis:

H2. *The development of digital finance urges relatively large-scale farmers to invest more in the agricultural field, promoting agricultural income.*

H3. *The development of digital finance promotes the off-farm transfer of agricultural labor and reduces agricultural income.*

H4. *The development of digital finance facilitates agricultural land rent-in and promotes agricultural income.*

3. Research Design

3.1. Data Sources

The household data used in this paper was released by China Labor Dynamics Survey (CLDS) data in 2016 and 2018. The survey was a large-scale comprehensive survey organized by Sun Yat-Sen University. The survey was carried out in the form of face-to-face interviews. Considering the significant regional differences in Chinese society, respondents were selected using a multistage, cluster, stratified Probability Proportional-to-Size (PPS) sampling technique. CLDS has interviewed households in 29 provinces, the information involves demographic, economy, society, and other aspects, which provide objective social science data for economic research.

Moreover, we used the Digital Financial Inclusion Index (DFII) of China, which was compiled by the Peking University Institute of Digital Finance and Ant Financial Services Group based on the big data from Ant Financial Services to reflect the development of digital finance. The index comprehensively examines the development of digital finance from various aspects, including the coverage breadth, the usage depth, and the degree of digitalization. Among them, the coverage breadth of digital finance uses the number of bank cards bound in digital accounts as an indicator; the usage depth is composed of six categories of indicators such as payment business, monetary fund business, and credit business; The digitization level is constructed according to four categories of indicators such as mobilization. The index covers 337 cities above the prefecture level and more than 2800 counties in 31 provinces in China from 2011 to 2020. The data of control variables at city level were drawn from the China City Statistical Yearbook.

Since rotating samples were conducted in the survey, there were no tracking samples to meet the requirements. According to research needs, we used mixed cross-sectional data from 2016 and 2018. This paper selects relatively large-scale farmers, excludes the samples that are not engaged in agricultural production and have no agricultural income, and the samples which are missing the main variables. According to data released by the third General Census of Agriculture, the average business scale of rural households in China is 0.52 ha, and there are 90% of rural households operating arable land of less than 0.66ha in 230 million rural households. Consistent with China's national conditions, most of the farmers surveyed in CLDS are smallholders. Meanwhile, following the study of Qian et al. [58], farmers with planting sizes over 0.66 ha are defined as relatively large-scale farmers in this paper. After omitting cases missing essential data, the final dataset comprised 2776 samples.

3.2. Variables

3.2.1. The Dependent Variable

We use gross margin as a proxy for agricultural income, which is obtained by subtracting the total agricultural operation cost from the total agricultural income. Agricultural income includes income from vegetables, orchards, forests, grains, livestock, animal husbandry, and fisheries. The logarithmic transformation is performed to fit skewed data distributions into a normal distribution.

3.2.2. The Core Independent Variable

We used the digital finance general index to measure the development of digital finance. This index is the most representative indicator, it has been widely used by many scholars [59,60]. Since this study selected the dependent variable from the questionnaire of CLDS2016 and 2018, and considering that the CLDS2016 and 2018 questionnaire surveyed the sample in 2015 and 2017, we applied the total index of China's digital finance at the prefecture-level in 2015 and 2017 to match the questionnaire of CLDS2016 and 2018.

3.2.3. The Mediating Variables

Agricultural production factors mainly include agricultural capital, land, and workforce. Agricultural capital is determined based on the operating costs for seed, fertilizer, pesticides, fuel, and machinery expenses (not capital investments), as well as service items such as machine hire, paid and unpaid labor, marketing, storage, and transportation. The agricultural workforce is the number of people who engage in agricultural production for more than three months within one year. Agricultural land is the total area used to cultivate crops and animal husbandry.

3.2.4. The Control Variables

Drawing on the existing literature [28,61] we controlled the following variables: At the individual level, including the household decision maker's gender, age, education, health condition; at the family level, we control for family size, political status, family dependency ratio, the share of females, partially or fully mechanized farming methods, and the farm type of farmers. At the village level, we control whether this village has a non-agricultural industry, whether the village provide agricultural services (including unified planting, pest control, and skill training), whether there is a bank facility, the distance between the village and the county center. At the prefecture level, the ratio of the primary industry is selected because they are potential confounders of their relationship with the agricultural income.

The definitions and descriptive statistics of each variable are listed in Table 1.

Table 1. The definitions and descriptive statistics of each variable.

Variables	Definition	Mean	S.D
	Dependent Variable		
Gross margin	The natural logarithm of the difference between total agricultural income and total agricultural operation cost	9.2085	1.6973
	Core Independent Variable		
Digital finance	Digital financial inclusion index.	184.7302	27.2802
	Mediation Variable		
Agricultural capital	The natural logarithm of the total cost of agricultural operation.	8.8677	1.1907
Agricultural workforce	The number of people engaged in agricultural production for more than three months within one year.	2.0904	0.8633
Agricultural land	The natural logarithm of the land is used to cultivate crops and animal husbandry.	3.0871	0.7682
	Individual Level		
Gender	Men = 1, Women = 0.	0.9135	0.2811
Age	The family decision maker's age.	52.4373	10.1482
Education	No schooling = 1, Primary school = 2, Junior high school = 3, High school = 4, University degree or above = 5.	2.5771	0.8093
Health	The family decision maker's health status. Very unhealthy = 1, Moderately unhealthy = 2, General = 3, Healthy = 4, Very healthy = 5	3.5973	0.1000
	Family Level		
Size	The number of members.	4.9640	2.1066
Female	The percentage of women in the family.	48.7483	14.3049
Depend	The proportion of young people aged 0-14 and the elderly persons over 65 in the family.	23.7897	21.1900
Status	The number of Communist Party or democratic party members in the family.	0.2158	0.5260
Mode	1 if partially or fully mechanized farming, 0 otherwise.	0.7911	0.4066
Farm type	Crop farming = 1, Breeding industry = 0	0.9546	0.2082
	Village Level		
Non-agricultural industry	1 if there is a non-agricultural industry in this village, 0 otherwise.	0.1153	0.3194
Bank	1 if there is a bank facility, 0 otherwise.	0.9564	0.2042
Distance	The natural logarithm of the distance from the village to the county center.	2.1678	0.9121
Service	1 if the village provide agricultural services, 0 otherwise	0.7727	0.4192
	Prefecture Level		
Primary industry	The ratio of the primary industry to total GDP in each city.	13.6011	7.3486

3.3. Method

Firstly, the ordinary least-square estimation method is used to explore the impact of digital finance on relatively large-scale farmers' agricultural income and test Hypothesis 1. Our empirical model can be represented as follows:

$$income_{it} = \alpha_0 + \alpha_1 digital_{it} + \alpha_2 x_{it} + \lambda_t + \varepsilon_{it} \quad (1)$$

where $income_i$ denotes farmer i's agricultural income; $digital_i$ denotes the digital finance index of the city where farmer i located; x_i is control variables; λ_t denotes the time fixed effect, and ε_{it} is the random error term of the model.

In order to examine Hypothesis 2–4, we construct the multiple intermediary effect model. The models are set as follows:

$$med_{it} = b_0 + b_1 digital_{it} + b_2 x_{it} + \lambda_t + \varepsilon_{it} \quad (2)$$

$$income_{it} = c_0 + c_1 digital_{it} + c_2 med_{it} + c_3 x_{it} + \lambda_t + \varepsilon_{it} \quad (3)$$

where med_i stands for the farmer i's agricultural capital, agricultural workforce, and land. On condition that b_1 is significant, if c_1 and c_2 are both significant at the 10% level and the value of c_1 is lower than α_1, it indicates that the mediating variable has played the role of a partial mediator; if c_1 is insignificant, but c_2 is still significant, there is a complete mediating effect. Even though the coefficients b_1 and c_2 are significantly non-zero, it does not ensure that the mediating effect $b_1 c_2$ is significantly non-zero at the same time; for this reason, this paper uses the Sobel test statistic for its robustness test.

4. Empirical Results

4.1. Main Findings of Basic Regression

To ensure the stability and accuracy of the benchmark test, this study adopts the heteroscedasticity robust standard error to prevent the possible heteroscedasticity problem. Table 2 displays the estimated results, indicating the impact of digital finance on relatively large-scale farmers' agricultural income is positive at the 1% significance level. We claim that Hypothesis 1 is confirmed. Digital finance does improve agricultural income. Nevertheless, the coefficient is 0.023. In terms of economic significance, every one unit increase in digital finance index can lead to an average increase of about 2.31% in agricultural income.

Table 2. Estimated results of digital finance index on the agricultural income.

Variables	Gross Margin
Digital finance	0.0231 *** (0.0030)
Gender	0.0403(0.1245)
Age	−0.0088 *** (0.0034)
Education	0.0825 * (0.0452)
Health	0.1605 *** (0.0310)
Size	0.0019(0.0142)
Female	0.0014(0.0026)
Depend	−0.0070 *** (0.0014)
Status	0.1494 *** (0.0496)
Mode	0.2520 *** (0.0808)
Farm type	−0.3215 * (0.1637)
Non-agricultural industry	−0.0507 (0.1177)
Bank	0.0015 (0.1230)
Distance	−0.0696 (0.0495)
Service	−0.0923 (0.0913)
Primary industry	0.0199 *** (0.0066)
Time fixed effects	Yes
Constant	4.9886 *** (0.6624)
Observations	2776
R-squared	0.0675

Notes: * and *** respectively indicate significance at the level of 10% and 1%; Heteroscedasticity robust standard errors are shown in parentheses.

In addition to the core independent variables that have significant impact on relatively large-scale farmers' agricultural income, a total of seven control variables also have significant impact on agricultural income. Specifically, education level, health status, number of party members, mechanized farming, and the proportion of primary industry positively promotes agricultural income. It is worth noting that the positive effect of household decision-makers' education on agricultural income reflects the importance of farmers' human capital. Therefore, in the context of digital transformation, more relatively large-scale farmers should be equipped with new agricultural knowledge and skills, while paying attention to the financial behavior characteristics of relatively large-scale farmers and improving their digital financial literacy. In contrast, age, dependency ratio, and farm type negatively impact agricultural income. The higher the dependency ratio and household decision maker's age, the less labor supply affects agricultural production. This result is in line with the former analysis. The non-agricultural industry in the village will cause the transfer of the agricultural workforce, thus substituting non-agricultural income for agricultural income.

4.2. Endogenous Problem and Robustness Test

4.2.1. Endogenous Problems

A critical problem in regression analysis is that the basic regression results may be endogenous: First, data entail a measurement error problem. Although the CLDS adopts proportional probability sampling (PPS) with stratification, multistage, multi-level, and population proportionality, there are inevitably data collection errors in the micro surveys. Second, theoretically, unobservable factors may affect agricultural income, resulting in estimation errors caused by missing variables. Third, the complex causal relationship between digital finance and agricultural income is still unclear for rural areas in different stages of digital finance development. A reverse causal relationship may exist: agricultural income may impact the use of digital finance, resulting in simultaneous bias. Therefore, this paper used instrumental variables to solve any other endogeneity problems that the above problems may cause.

In order to avoid any other possible endogeneity problems, this study selects "the average value of the digital financial index of other counties in the province where the farmer is located except this city" as the instrumental variable of the digital financial index of the city where the farmer is located. The selection of this instrumental variable is based on the following considerations: First, the development level of digital finance in this city is related to the development of digital finance in other cities in the province. Moreover, due to the low liquidity of relatively large-scale farmers, there is no direct relationship between the development of digital finance in other cities and relatively large-scale farmers' agricultural income, which meets the exogenous requirements of instrumental variables. Therefore, we carried out a two-stage least squares (2SLS) estimation using the internet as the instrumental variable for digital finance. Table 3 column (1) shows that in the first-stage regression, the instrumental variable has a significant impact on the independent variable, satisfying the correlation requirements for the instrumental variable. As shown in column (2) in Table 3, the value of the Cragg–Wald F statistic is 128.594, which is larger than the critical value at the 10% level of the Stock–Yogo weak identification test in parentheses, representing that the instrumental variable is not a weak instrumental variable. Therefore, this IV had good properties. The results of IV regression indicating the previous conclusions are robust.

Table 3. Estimated results of IV-2SLS.

	(1) **The First Stage**	**(2)** **The Second Stage**
	Digital Finance	**Agricultural Income**
IV	0.2002 *** (0.0189)	
Digital finance		0.0500 *** (0.0150)
Control variables	Yes	Yes
Year fixed effects	Yes	Yes
Cragg–Wald F statistic		128.594
10% max IV size		16.38
Observations	2766	2766

Notes: *** respectively indicate significance at the level of 1%; Heteroscedasticity robust standard errors are shown in parentheses.

4.2.2. Robustness Test

To further check the robustness of the model estimation results, three strategies were implemented: replacing core explanatory variables, removing extreme values, and adding control variables.

First, replace the explanatory variable. Drawing on the method proposed by Cao et al. [62], considering the cyclical nature of agricultural production, there may be a lag in the impact of digital finance on agricultural income. This study replaced the independent variable with one-period-lagged independent variable, namely the digital finance index for 2014 and 2016. As shown in column (1) in Table 4, the one-period-lagged digital finance index could significantly improve relatively large-scale farmers' agricultural income. The benchmark regression results still hold.

Table 4. Robustness tests by substituting independent variable and eliminating extreme values.

	Gross Margin	
	(1) Substitute Independent Variable	**(2) Eliminate Extreme Values**
One-period-lagged	0.0249 *** (0.0031)	
Digital finance		0.0229 *** (0.0030)
Control variables	Yes	Yes
Year fixed effects	Yes	Yes
Observations	2766	2766
R-squared	0.0704	0.0675

Notes: *** respectively indicate significance at the level of 1%; Heteroscedasticity robust standard errors are shown in parentheses.

Second, to reduce the influence of extreme values, we winsorized the agricultural income at the bottom and top 1% of their distributions. We eliminated one percent of samples at both ends for robustness check. The results are shown in column (2) in Table 4; the digital finance still has a positive effect on agricultural income, confirming the robustness of the benchmark results.

Third, from the agricultural land and agricultural workforce perspective, land registration and certification and whether the village organizes farmers to work are added to the regression. In Table 5 column 1, we added the variable of land registration and certification; the proxy variable is the question in CLDS: "Has your family received the Rural land Contractual Management Right Certificate?". Valued 1 if the respondent has answered Yes, 0 otherwise. In Table 5 column 2, we added the variable of whether the village organizes farmers to work, and the proxy variable of the latter one is the question: "Are there any agents organizing jobs for farmers?". Valued 1 if the answer is Yes, 0 otherwise. The regression results are shown in Table 5, and the previous conclusions are robust.

Table 5. Robustness tests by adding variables.

	Gross Margin	
	(1) Confirmation of Agricultural Land Rights	**(2) Organize Labor to Go Out to Work**
Digital finance	0.0251 *** (0.0032)	0.0219 *** (0.0031)
Control variables	Yes	Yes
Year fixed effects	Yes	Yes
Observations	2766	2766
R-squared	0.0833	0.0688

Notes: *** respectively indicate significance at the level of 1%; Heteroscedasticity robust standard errors are shown in parentheses.

4.3. Mediation Effect Analysis

The above theoretical part analyzes the mediation role of agricultural production factors between digital finance and agricultural income. Next, we intend to examine the three potential influencing channels of digital finance on agriculture income by the sequential test method. Since gross margin = total agricultural income-total agricultural operation cost, and agricultural capital are the operating costs. To avoid multicollinearity, we replace gross margin with agricultural income as the independent variable in this section. The results are shown in Tables 6 and 7.

Table 6. Digital finance and agricultural production factors.

	(1) **Agricultural Income**	**(2)** **Agricultural Capital**	**(3)** **Agricultural Workforce**	**(4)** **Agricultural Land**
Digital Finance	0.0157 ***	0.0177 ***	−0.0042 ***	0.0058 ***
	(0.0019)	(0.0020)	(0.0015)	(0.0012)
Control variables	Yes	Yes	Yes	Yes
Constant	7.2000 ***	6.7766 ***	2.2647 ***	1.7733 ***
	(0.4125)	(0.4233)	(0.3130)	(0.2717)
Year fixed effects	Yes	Yes	Yes	Yes
Observations	2776	2776	2766	2776
R-squared	0.1346	0.1399	0.0809	0.1006

Notes: *** respectively indicate significance at the level of 1%; Heteroscedasticity robust standard errors are shown in parentheses.

Table 7. Digital finance, agricultural production factors, and agricultural income.

	Agricultural Income		
	(1)	**(2)**	**(3)**
Digital Finance	0.0035 ***	0.0161 ***	0.0123 ***
	(0.0013)	(0.0018)	(0.0017)
Agricultural Capital	0.6900 ***		
	(0.0161)		
Agricultural Workforce		0.0940 ***	
		(0.0262)	
Agricultural Land			0.5966 ***
			(0.0287)
Control variables	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Constant	2.5243 ***	6.9872 ***	6.1420 ***
	(0.3306)	(0.4150)	(0.3923)
Sobel Z	8.771 ***	−2.266 **	4.368 ***
The ratio of mediation effect	77.48%	2.50%	22.10%
Observations	2776	2776	2776
R-squared	0.5721	0.1392	0.2770

Notes: ** and *** respectively indicate significance at the level of 5% and 1%; Heteroscedasticity robust standard errors are shown in parentheses.

Firstly, examine whether digital finance can influence agricultural income through agricultural capital investment. It is shown in column (1) of Table 6 that the coefficient of digital finance is positive and significant at the 1% level. The results in column (2) of Table 6 show that the coefficient of the impact of digital finance on agriculture capital is positive, indicating that digital finance has promoted relatively large-scale farmers' agriculture capital investment. The results in column (1) in Table 7 show that agriculture capital has a significantly positive impact on agriculture income. Meanwhile, after adding the variable of agricultural capital, the coefficient of the impact of digital finance on agricultural income is still significant, suggesting that agriculture capital has a certain mediating effect. Hypothesis 2 is verified. The results of the Sobel mediating effect test show that the effect of agriculture capital as a mediating variable is positive at the 1% significance level, and the mediating effect size is 77.48%, the largest one, which reveals the importance of agricultural capital in promoting agricultural income compared with other production factors.

Secondly, examine whether digital finance can influence agricultural income through the agricultural workforce. Digital finance has a significantly negative influence on the agricultural labor force (see column 3 in Table 6); at the same time, the agricultural labor force has a significant impact on agricultural income and the coefficient is positive (see column 2 in Table 7). In addition, after joining the intermediary variable agricultural workforce, digital finance still has a significant positive impact on agricultural income, which fits Hypothesis 3. However, the results of the Sobel mediating effect test show the mediating effect value of agricultural workforce accounting only for 2.50% of the total effect, which is the weakest in the mediating variables. It may be that with the non-agricultural transfer of labor, farmers may choose to purchase agricultural machinery [62] or outsourced agricultural mechanization services to cope with the labor shortage in agricultural production [63].

Thirdly, examine whether digital finance can influence agricultural income through agricultural land. As we can see from column (4) in Table 6 and column (3) in Table 7. Digital finance has a significantly positive influence on agricultural land, and after adding the intermediary variable agricultural land into regression, the coefficient of digital finance and agricultural land both are positive. It suggests that digital finance can indirectly facilitate agricultural income through promoting rent-in land. The Sobel test indicates that 22.10% of the effect of digital finance on agricultural income is through the promotion of agricultural land. Hypothesis 4 is verified.

Through the discussion of the above mechanisms, this paper finds that there are two positive mechanisms for expanding agricultural capital and agricultural land, and a negative mechanism for reducing agricultural labor in the channels that digital finance affects the agricultural income of relatively large-scale farmers. However, in general, digital finance still has a significant effect on agricultural income.

5. Heterogeneity

5.1. Heterogeneity Analysis Based on Agricultural Services

China has a vast territory; there are significant differences between regions in terms of natural and cultural environment and agricultural production and farming conditions. The agricultural services for farmers in different areas are not uniform, including agricultural materials supply, unified planting, pest control, and machinery. As the service improves the efficiency of agricultural technology, agricultural service has been unanimously welcomed by farmers in China [64]. Column 1 and 2 in Table 8 present that digital finance significantly positively impacts agricultural income for relatively large-scale farmers who receive both pest control and unified planting planning services. With agriculture services, it is more conducive for relatively large-scale farmers who access to digital finance to overcome the drawbacks of land fragmentation, control natural risks to a certain extent, reduce operating costs, and expand crop output. Digital finance could fully play the income-increasing effect.

Table 8. Estimated results of different categories according to whether receiving agricultural service or not.

	Gross Margin			
	(1) Receiving Service	**(2) No Service**	**(3) Receiving Skill Training**	**(4) No Skill Training**
Digital finance	0.0274 ***	0.0217 ***	0.0229 ***	0.0175 ***
	(0.0063)	(0.0033)	(0.0040)	(0.0047)
Control variables	Yes	Yes	Yes	Yes
Constant	3.0818 ***	5.6774 ***	4.8823 ***	5.9753 ***
	(1.3707)	(0.7395)	(0.9096)	(1.0387)
Year fixed effects	Yes	Yes	Yes	Yes
Observations	524	2252	1543	1233
R-squared	0.1546	0.0616	0.0749	0.0825

Notes: *** respectively indicate significance at the level of 1%; Heteroscedasticity robust standard errors are shown in parentheses.

5.2. Heterogeneity Analysis Based on Human Capital

The technical perception of farmers could be enhanced via training in the economic, scientific, and technical. For relatively large-scale farmers, agricultural production skills are their important human capital. The improvement of agricultural production skills can help improve agricultural productivity and the quality of agricultural products. Therefore, we divided the samples into two groups according to whether they obtained agricultural skills training or not. Columns 3 and 4 of Table 8 show that farmers who receive agricultural skills training can strengthen the positive impact of digital finance on agricultural income. Therefore, to give full play to the increasing effect of digital finance on agricultural income, attention should be paid to the training of agricultural production skills for relatively large-scale farmers.

5.3. Heterogeneity Analysis Based on Breeding Industry, Grain Crop, and Cash Crop

Finally, different agricultural production fields require different input factors; we divide agricultural production into the breeding industry, grain crop, and cash crop. From Table 9 we can see that digital finance has a significant positive impact on cash crops. However, the impact on grain crops is not significant. Moreover, digital finance has a negative but insignificant impact on the breeding industry. The breeding industry is increasingly tending to large-scale development with a high technical level and abundant capital. For farmers, it is harder to enter into the breeding industry than the crop industry. Currently, the scale of digital finance is smaller than traditional finance, and the economic benefits of digital finance for cash crops are stronger than for grain crops, so farmers as rational economic actors, pursue the maximization of their interests, who participating in digital finance are more inclined to invest their funds in the cash crop. Therefore, in the context of digital finance, the local government should optimize and adjust the planting structure on the premise of respecting the wishes of farmers and being guided by market demand to ensure food security and help farmers increase their income.

Table 9. Estimated results of different categories according to the types of agricultural production.

	Gross Margin		
	(1) Breeding	**(2) Grain Crop**	**(3) Cash Crop**
Digital finance	−0.0062	0.0037	0.0457 ***
	(0.0258)	(0.0044)	(0.0138)
Control variables	Yes	Yes	Yes
Constant	8.6918 ***	6.6769 ***	4.3803 ***
	(4.6717)	(0.9121)	(2.9828)
Year fixed effects	Yes	Yes	Yes
Observations	317	2773	647
R-squared	0.0657	0.1974	0.1645

Notes: *** respectively indicate significance at the level of 1%; Heteroscedasticity robust standard errors are shown in parentheses.

6. Conclusions and Discussions

Digital finance could change the allocation of agricultural production factors of relatively large-scale farmers with different endowments, thus affecting agricultural income. Based on the data from CLDS 2016 and 2018, this paper uses the multiple intermediary effect model to reveal how digital finance impacts agricultural income from the perspective of factor allocation. The present study's findings show that: (1) digital finance promotes relatively large-scale farmers' agricultural income significantly; (2) agricultural capital, agricultural land, and agricultural workforce play a partial mediating role between digital finance and relatively large-scale farmers' agricultural income. However, the mediating role of the agricultural workforce is the weakest, and the mediating role of agricultural capital is the strongest in the three mediation variables; that is, relatively large-scale farmers participating in digital finance are more inclined to invest more in the agricultural field to gain more income. The sustainable financial transformation driven by digital technologies offers new opportunities for the agricultural sector. Digital finance can provide sufficient financial power for agricultural industrialization. Agricultural modernization and rural revitalization in China are designed to increase yields and incomes, with the transformation focusing on the means of production and technological development rather than on laborers. The development of intensive smart farming and the application of agricultural information technology will continue to displace the agricultural workforce. However, the demand for professional farmers will undoubtedly be more urgent. This result further confirms that the mediating role of agricultural land is more significant than the workforce. Promoting rent-in land for professional farmers is beneficial to gaining scale economy; and (3) considering the heterogeneity, further analysis finds that the development of digital finance has a more significant positive impact on the agricultural income for relatively large-scale farmers who receive agricultural skill training, agricultural service, and engage in the crop industry instead of the breeding industry. Even though this study only concerns the impact of digital finance on agricultural income in China, our findings can have important implications for countries urgently needing high-quality development.

This study has several policy implications. First, it underscores the need to develop digital finance. Digital finance provides an important scenario platform with which financial institutions could continuously innovate the modes and means to match and offer better support for agriculture. The policy maker should give full policy support to vigorously improve the digital infrastructure to address barriers attributed to the digital divide, especially in the rural area and those areas with poor natural endowments. Second, implement appropriate policy preference for new forms of financial services, expand the agricultural credits for the farming sector, and release new vitality for high-quality development of the agricultural economy. Third, actively cultivate a group of new business entities and family farms with modern business concepts, which is beneficial to rent-in agricultural land and realize moderate-scale agriculture. Fourth, farmer training programs typically result in human capital acquisition. The government should emphasize providing more targeted programs and specific training for farmers and be in charge of implementing measures for cultivating new professional farmers.

There are still some limitations in this paper. China's digital finance development is currently leading in the world. Whether the experience of the Chinese in supporting agricultural development with digital finance can be applied to other countries remains to be seen. Furthermore, we argue that the mechanisms of how mobile payment, online credit, online insurance, and online wealth management impact agricultural income are different. This could be an excellent opportunity for future research to investigate.

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References

1. Xue, J.L. Characteristics and limitations of agricultural land management behavior of super small-scale farmers. *Econ. Manag.* **2018**, *32*, 24–29.

2. Ye, J. Land transfer and the pursuit of agricultural modernization in China. *J. Agrar. Change* **2015**, *15*, 314–337. [CrossRef]
3. Addison, M.; Ohene-Yankyera, K.; Aidoo, R. Quantifying the impact of agricultural technology usage on intra-household time allocation: Empirical evidence from rice farmers in Ghana. *Technol. Soc.* **2020**, *63*, 101434. [CrossRef]
4. Li, X.; Liu, J.; Huo, X. Impacts of tenure security and market-oriented allocation of farmland on agricultural productivity: Evidence from China's apple growers. *Land Use Policy* **2021**, *102*, 105233. [CrossRef]
5. Giné, X. Access to Capital in Rural Thailand: An Estimated Model of Formal vs. Informal Credit. *J. Dev. Ecom.* **2011**, *96*, 16–29. Available online: https://EconPapers.repec.org/RePEc:eee:deveco:v:96:y:2011:i:1:p:16-29 (accessed on 13 July 2010). [CrossRef]
6. Nakano, Y.; Magezi, E.F. The impact of microcredit on agricultural technology adoption and productivity: Evidence from randomized control trial in Tanzania. *World Dev.* **2020**, *133*, 104997. [CrossRef]
7. Amin, S.; Rai, A.S.; Topa, G. Does microcredit reach the poor and vulnerable? Evidence from northern Bangladesh. *J. Dev. Econ.* **2003**, *70*, 59–82. [CrossRef]
8. Laffont, J.J.; Tirole, J. The Politics of government decision-making: A theory of regulatory capture. *Q. J. Econ.* **1991**, *106*, 1089–1127. [CrossRef]
9. Platteau, J.P. Monitoring elite capture in community-driven development. *Dev Change* **2004**, *35*, 223–246. [CrossRef]
10. Galor, O.; Zeira, J. Income distribution and macroeconomics. *Rev. Econ. Stud.* **1993**, *60*, 35–52. [CrossRef]
11. Abate, G.T.; Rashid, S.; Borzag, C.; Getnet, K. Rural finance and agricultural technology adoption in Ethiopia: Does the institutional design of lending organizations matter? *World Dev.* **2016**, *84*, 235–253. [CrossRef]
12. Liu, G.; Fang, H.; Gong, X.; Wang, F.F. Inclusive finance, industrial structure upgrading and farmers' income: Empirical analysis based on provincial panel data in China. *PLoS ONE* **2021**, *16*, e0258860. [CrossRef] [PubMed]
13. World Bank Report. *ICT for Greater Development Impact: World Bank Group Strategy for Information and Communication Technology*; World Bank: Washington, DC, USA, 2012. Available online: https://openknowledge.worldbank.org/bitstream/handle/10986/27411/%20715400WP0WBG0I0sclosed0July02502012.pdf?sequence=1&isAllowed%20=%20y (accessed on 25 July 2012).
14. Agwu, M.E. Can technology bridge the gap between rural development and financial inclusions? *Technol. Anal. Strateg. Manag.* **2021**, *33*, 123–133. [CrossRef]
15. Huang, Z. *The Power of Digital Finance: Empowering the Real Economy*; People's University of China Press: Beijing, China, 2018.
16. Petrakis, Y.; Collins, L. Crowdfunding: A New Innovative Model of Providing Funding to Projects and Businesses. 2013. Available online: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2395226 (accessed on 5 May 2013).
17. Wang, X.; He, G. Digital financial inclusion and farmers' vulnerability to poverty: Evidence from rural China. *Sustainability* **2020**, *12*, 1668. [CrossRef]
18. Ozil, P.K. Impact of digital finance on financial inclusion and stability. *Borsa Istanb Rev.* **2018**, *18*, 329–340. [CrossRef]
19. Cortina Lorente, J.J.; Schmukler, S.L. The Fintech Revolution: A Threat to Global Banking? *World Bank Res. Policy Briefs*. 2018, p. 125038. Available online: https://ssrn.com/abstract=3255725 (accessed on 1 March 2018).
20. Zhong, W.; Jiang, T. Can internet finance alleviate the exclusiveness of traditional finance? Evidence from Chinese P2P lending markets. *Financ. Res. Lett.* **2021**, *40*, 101731. [CrossRef]
21. He, J.; Li, Q. Can online social interaction improve the digital finance participation of rural households? *China Agric. Econ. Rev.* **2020**, *12*, 295–313. [CrossRef]
22. Sarma, M.; Pais, J. Financial inclusion and development. *J. Int. Dev.* **2011**, *23*, 613–628. [CrossRef]
23. Anand, S.K.; Chhikara, K.S. A theoretical and quantitative analysis of financial inclusion and economic growth. *Manag. Labour Stud.* **2013**, *38*, 103–133.
24. Yu, N.; Wang, Y. Can Digital Inclusive Finance Narrow the Chinese Urban-Rural Income Gap? The Perspective of the Regional Urban-Rural Income Structure. *Sustainability* **2021**, *13*, 6427. [CrossRef]
25. Huang, Y.P.; Xu, W. Building an efficient financial system in China: A need for stronger market discipline. *Asian Econ Policy R.* **2017**, *12*, 188–205. [CrossRef]
26. Suri, T.; Bharadwaj, P.; Jack, W. Fintech and household resilience to shocks: Evidence from digital loans in Kenya. *J. Dev. Econ.* **2021**, *153*, 102697. [CrossRef]
27. Uduji, J.I.; Okolo-Obasi, E.N.; Asongu, S. Electronic wallet technology and the enabling environment of smallholder farmers in Nigeria. *Agric. Financ. Rev.* **2019**, *79*, 666–688. [CrossRef]
28. Liu, Y.; Liu, C.; Zhou, M. Does digital inclusive finance promote agricultural production for rural households in China? Research-based on the Chinese family database (CFD). *China Agric. Econ. Rev.* **2021**, *13*, 475–494. [CrossRef]
29. Zhao, P.; Zhang, W.; Cai, W.; Liu, T. The impact of digital finance use on sustainable agricultural practices adoption among smallholder farmers: An evidence from rural China. *Int. J. Environ. Res. Public Health* **2022**, *29*, 39281–39294. [CrossRef]
30. Manda, J.; Alene, A.D.; Gardebroek, C.; Kassie, M.; Tembo, G. Adoption and impacts of sustainable agricultural practices on maize yields and incomes: Evidence from rural Zambia. *J. Agric. Econ.* **2016**, *67*, 130–153. [CrossRef]
31. Shenoy, A. Market Failures and Misallocation. *J. Dev. Econ.* **2017**, *128*, 65–80. [CrossRef]
32. Sheng, Y.; Jackson, T.; Gooday, P. Resource reallocation and its contribution to productivity growth in Australian broadacre agriculture. *Aust. J. Agric. Resour. Econ.* **2017**, *61*, 56–75. [CrossRef]
33. Demertzis, M.; Merler, S.; Wolff, G.B. Capital markets union and the fintech opportunity. *J. Financ. Regul.* **2018**, *4*, 157–165. [CrossRef]

34. Manyika, J.; Lund, S.; Singer, M.; White, O.; Berry, C. *Digital Finance for All: Powering Inclusive Growth in Emerging Economies*; McKinsey Global Institute: New York, NY, USA, 2016; pp. 1–15.
35. Fu, Q.Z.; Huang, Y.P. Digital finances heterogeneous effects on rural financial demand: Evidence from China household finance survey and inclusive digital finance index. *J. Financ. Res.* **2018**, *11*, 68–84.
36. Wang, G.Z.; Jiang, G.H. Research on the innovative model of 'agricultural value chain þ Internet finance': Taking Nongfu loan and Beijing agricultural loan as examples. *Rural Econ.* **2017**, *4*, 49–55.
37. Jiang, W.G.; Li, L.Q. Financing model innovation of new agricultural management entities under the background of Internet banking in China. *Financ. Econ.* **2015**, *8*, 1–12.
38. Berger, A.N.; Udell, G.F. A more complete conceptual framework for SME finance. *J. Bank Financ.* **2006**, *30*, 2945–2966. [CrossRef]
39. Mollick, E. The dynamics of crowdfunding: An exploratory study. *J. Bus. Ventur.* **2014**, *29*, 1–16. [CrossRef]
40. Bruett, T.; Cows, K.; Com, P. How Disintermediation and the Internet are Changing Microfinance. *Community Dev. Invest. Rev.* **2007**, *3*, 44–50.
41. Carter, M.R. The impact of credit on peasant productivity and differentiation in Nicaragua. *J. Dev. Econ.* **1989**, *31*, 13–36. [CrossRef]
42. Fitz, D. Evaluating the impact of market-assisted land reform in Brazil. *World Dev.* **2018**, *103*, 255–267. [CrossRef]
43. Laeven, L.; Levine, R.; Michalopoulos, S. Financial innovation and endogenous growth. *J. Financ. Intermed.* **2015**, *24*, 1–24. [CrossRef]
44. Cao, S.; Nie, L.; Sun, H.; Sun, W.; Taghizadeh-Hesary, F. Digital finance, green technological innovation and energy-environmental performance: Evidence from China's regional economies. *J. Clean. Prod.* **2021**, *327*, 129458. [CrossRef]
45. Alene, A.D.; Coulibaly, O. The impact of agricultural research on productivity and poverty in Sub-Saharan Africa. *Food Policy* **2009**, *34*, 198–209. [CrossRef]
46. Gopinath, M.; Kennedy, P.L. Agricultural trade and productivity growth: A state-level analysis. *Am. J. Agric. Econ.* **2000**, *82*, 1213–1218. [CrossRef]
47. Sekabira, H.; Qaim, M. Mobile money, agricultural marketing, and off-farm income in Uganda. *Agric. Econ-Blackwell* **2017**, *48*, 597–611. [CrossRef]
48. Brynjolfsson, E.; Hu, Y.J.; Smith, M.D. From Niches to Riches: Anatomy of the Long Tail. *Sloan Manag. Rev.* **2006**, *47*, 67–71. Available online: https://ssrn.com/abstract=918142 (accessed on 21 July 2006).
49. Zhong, Y.; Lai, I.K.W.; Guo, F.; Tang, H. Research on government subsidy strategies for the development of agricultural products E-commerce. *Agriculture* **2021**, *11*, 1152. [CrossRef]
50. Kikulwe, E.M.; Fischer, E.; Qaim, M. Mobile money, smallholder farmers, and household welfare in Kenya. *PLoS ONE* **2014**, *9*, e109804. [CrossRef]
51. Cochrane, W.W. *Farm Prices: Myth and Reality*; U of Minnestoa Press: Minneapolis, MN, America, 1958.
52. Fousekis, P.; Pantzios, C. Output price risk and productivity growth in Greek agriculture. *Spoudai* **2000**, *50*, 106–124.
53. Allen, F.; Demirguc-kunt, A.; Klapper, L.; Peria, M.S.M. The foundations of financial inclusion: Understanding ownership and use of formal accounts. *J. Financ. Intermed.* **2016**, *27*, 1–30. [CrossRef]
54. Liu, Z.; Zhang, Y.; Li, H. Digital inclusive finance, multidimensional education, and farmers' entrepreneurial behavior. *Math Probl Eng.* **2021**, *2021*, 6541437. [CrossRef]
55. Tan, J.; Cai, D.; Han, K.; Zhou, K. Understanding peasant household's land transfer decision-making: A perspective of financial literacy. *Land Use Policy* **2022**, *119*, 106189. [CrossRef]
56. Miao, R.; Hennessy, D.A.; Feng, H. Effects of crop insurance subsidies and sod saver on land-use change. *J. Agric. Resour. Econ.* **2012**, *41*, 247–265. [CrossRef]
57. Mathijs, E.; Nov, N. Subsistence farming in central and Eastern Europe: Empirical evidence from Albania, Bulgaria, Hungary, and Romania. *East. Eur. Econ.* **2004**, *42*, 72–89. [CrossRef]
58. Qian, L.; Lu, H.; Gao, Q.; Lu, H.L. Household-owned farm machinery vs. outsourced machinery services: The impact of agricultural mechanization on the land leasing behavior of relatively large-scale farmers in China. *Land Use Policy* **2022**, *115*, 106008. [CrossRef]
59. Guo, F.; Wang, J.Y.; Wang, F.; Kong, T.; Zhang, X.; Cheng, Z.Y. Measuring China's digital financial inclusion: Index compilation and spatial characteristics. *China Econ. Q.* **2020**, *19*, 1401–1418.
60. Zhang, X.; Yang, T.; Wang, C.; Wan, G.H. Digital finance and household consumption: Theory and evidence from China. *Manag. World* **2020**, *36*, 48–63.
61. Zhou, Z.; Zhang, Y.; Yan, Z. Will Digital Financial Inclusion Increase Chinese Farmers' Willingness to Adopt Agricultural Technology. *Agriculture* **2022**, *12*, 1514. [CrossRef]
62. Ji, Y.; Yu, X.; Zhong, F. Machinery investment decision and off-farm employment in rural China. *China Econ. Rev.* **2012**, *23*, 71–80. [CrossRef]
63. Ma, W.; Renwick, A.; Grafton, Q. Farm machinery use, off-farm employment and farm performance in China. *Aust. J. Agric. Resour. Econ.* **2018**, *62*, 279–298. [CrossRef]
64. Zheng, H.; Ma, W.; Guo, Y.; Zhou, X. Interactive relationship between non-farm employment and mechanization service expenditure in rural China. *China Agric. Econ. Rev.* **2021**, *14*, 84–105. [CrossRef]