

Article

Does the Use of Digital Finance Affect Household Farmland Transfer-Out?

Haibo Lei ^{1,2,*} and Qin Su ¹

¹ School of Banking and Finance, University of International Business and Economics, Beijing 100029, China; suqin@uibe.edu.cn

² School of Economics and Management, Tianjin University of Technology and Education, Tianjin 300222, China

* Correspondence: yutian_lei@126.com

Abstract: Digital finance offers opportunities for inclusive growth in rural areas. This study aims to clarify how digital financiers affect farmland transfer-out. Using the data from the China Household Finance Survey in 2015, this paper establishes Probit and Tobit models to empirically analyze the impact and mechanisms of digital finance on household farmland transfer-out. The study finds that digital financial use significantly increases the probability and proportion of farmland transfer-out and that this effect is greater among households with older heads and lower household per capita income and financial accessibility, suggesting that digital finance has an important role to play in reducing inequality and promoting inclusive growth. Further analysis reveals that off-farm employment and information channels are mediating mechanisms through which digital finance facilitates farmland transfer. Specifically, on the one hand, the financial function of digital finance increases the share of employment and entrepreneurship among rural households. In terms of industry and skill type, digital finance promotes the entry of farmers into tertiary employment, facilitates off-farm employment for low and medium-skilled farmers, and has no impact on the employment of high-skilled farmers. On the other hand, the information function accompanying digital finance broadens households' access to information, both of which have a favorable effect on farmland transfer-out. This study provides new ideas for supporting agricultural land transfer from a digital finance perspective.

Keywords: digital finance; farmland transfer-out; off-farm employment; information channels



Citation: Lei, H.; Su, Q. Does the Use of Digital Finance Affect Household Farmland Transfer-Out? *Sustainability* **2023**, *15*, 12103. <https://doi.org/10.3390/su151612103>

Academic Editors: Weixin Yang and Yunpeng Yang

Received: 15 July 2023

Revised: 5 August 2023

Accepted: 6 August 2023

Published: 8 August 2023



Copyright: © 2023 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

Land is the most essential element for food security and a core resource for economic development especially for developing countries with large populations such as China [1]. The fundamental predicament in China is the conflict between people and the land. China has to support up to 20% of the world's population yet only possesses 9% of the world's arable land. Since the late 1970s, China has gradually established the household contract responsibility system, realizing the "separation of rights" between the collective ownership of contracted land and the contracted management rights of farming households. The household contract responsibility system mobilized the production enthusiasm of farmers, adapted to the needs of economic development at the time, and addressed the issue of Chinese farmers' access to food and clothing. However, the fragmentation of farmland caused by the equal distribution of land contracts in rural areas has severely impeded the advancement of China's agricultural modernization.

Land transfer and moderate-scale operation are necessary to develop modern agriculture, which can optimize land resource allocation and improve productivity [2,3]. To promote the sustainable utilization of land and the sustainable development of agriculture, China has continuously improved its land transfer policy. In March 2003, the Rural Land Contracting Law of the People's Republic of China was formally promulgated, and since

then, the transfer of land management rights has entered a period of legal protection and policy support. Since 2013, China has reformed its land ownership system. Based on the household contract responsibility system, China has gradually established a “three-rights” pattern of rural land ownership, land contracting rights, and land management rights, whereby the ownership of rural land belongs to the collectives, while farmers have the right to land contracting and are allowed to transfer the right to land management. Land transfer in this paper refers to the transfer of land management rights. According to the Civil Code of the People’s Republic of China, land management rights holders have the right to occupy rural land for a contractually agreed period of time, to carry out agricultural production and management on their own, and to obtain income.

In recent years under the government’s vigorous promotion, the scale of agricultural land transfer in China has been growing rapidly, and the transfer proportion of farmland increased from 18% in 2011 to 37% in 2017, then decreased to 34% in 2020. However, compared with the urgent demand for intensive land use, the marketability of agricultural land elements in China is not high, and the scale and efficiency of agricultural land transfer still need to be improved. There is an urgent need to further explore new driving forces to promote land transfer [4].

Some of the literature has explored the factors that drive land management rights transfer, such as personal experience [5], financial literacy [6], labor mobility [7], Internet use [8], agricultural mechanization [9], and property rights systems [10]. However, the literature has not yet focused on the relationship between digital finance and farmland transfer.

Digital finance broadly refers to the use of digital technology by traditional financial institutions and Internet companies to achieve financing, payment, investment, and other new financial business models [11–13]. Enhancing financial inclusion is the primary goal of digital finance, a new financial sector created by the fusion of digital technology and traditional conventional financial practices [14]. In contrast to traditional finance, digital finance can effectively address the issues of challenging risk control and the high cost of traditional financial services and serve a wider customer base, especially for long-tail customers [15]. As a result, there is an international consensus to enhance financial inclusion with the help of digital technology. The G20 High-Level Principles for Digital Financial Inclusion, released by the G20 Global Partnership for Financial Inclusion (GPII) in 2016, encourages countries to develop national action plans based on their specific national conditions to realize the huge potential that digital technology has for financial services.

Since 2013, China’s digital finance has developed rapidly and the degree of penetration in the social economy is gradually growing. According to the China Internet Network Information Center’s Statistical Report on the Development Status of China’s Internet Network, as of December 2021, there were 903 million Internet payment users, accounting for 87.6% of the total number of Internet users, and 190 million Internet finance users, accounting for 18.8% of the total number of Internet users in China.

Finance is the core of the modern economy, an important force for economic and social development, and a key resource for microeconomic units to achieve optimal goals. High transaction costs are a key barrier to access to financial services for low-income groups [16,17]. Digital finance reduces the cost of using financial services, enhances financial accessibility for rural residents [18], and provides rural households with more livelihood options, thereby reducing the importance of land-based agricultural production and inducing a reconfiguration of household factors.

A few pieces of the literature have discussed how access to credit affects the willingness and behavior of farmland market participants and found that access to credit is more conducive to households renting out farmland, which provides enlightenment for this study. However, this literature focuses on traditional finance and does not explore the internal mechanism [19,20].

Against the backdrop of the rapid growth of digital technologies in most parts of the world, how is digital finance affecting household farmland transfers? Are vulnerable farmers benefiting more? What are the mechanisms of action? Answers to these questions

will help to understand the relationship between digital finance and farmland transfer in more depth and provide decision support for promoting the sustainable use of farmland from the perspective of digital finance.

Based on the above considerations, this study analyzes and tests the effect of digital financial use on household farmland transfer-out using data from the 2015 China Household Finance Survey. It finds that digital financial use significantly increases the probability of land transfer-out and the proportion of transfer-out for households and that this effect is greater among households with older heads of household and lower per capita household income and financial accessibility, indicating that digital finance has an important role to play in reducing inequality and promoting inclusive growth. Mechanistic analyses reveal that off-farm employment and information channels are mediating mechanisms for digital financial use to promote household land transfer-out.

The main contributions of this paper are as follows: firstly, previous studies on the influencing factors of agricultural land transfer have neglected digital finance. With the increasing popularity of the concept of digital financial inclusion, the impact of digital finance has become more widespread. Based on large-scale survey data in China, this paper investigates the relationship between digital finance and farmland transfer decision-making, which can provide a new perspective for the study of the driving factors of farmland transfer. Second, this study analyses the mechanisms by which digital finance affects farmland transfer and finds that non-farm employment and information effects are important mediating mechanisms, which complements previous studies in the literature and contributes to a more in-depth understanding of the impact of digital finance. Third, this paper analyses the heterogeneous impacts in terms of age of household head, per capita household income, and financial accessibility, and the findings further confirm the poverty reduction effect of digital finance, providing new evidence that digital finance reduces inequality.

The subsequent part of this paper is organized as follows: the second part conducts the theoretical analysis and presents the research hypothesis; the third part is the research design, introducing the data sources, model setting, and descriptive statistics; the fourth part is the empirical results; the fifth part is the mechanism analysis; and the sixth part is the conclusion.

2. Theoretical Analysis

2.1. Digital Finance and Farmland Transfer

Under the conditions of a closed smallholder economy, farming is the only way for rural households to deploy their labor, and agricultural production becomes the main source of income for farming households. In the context of China's underdeveloped rural social security system, land is not only the main livelihood asset of households but also the main form of social security for the majority of rural households [21,22]. By cultivating the land, households can acquire fundamental livelihood security, performing a function similar to unemployment insurance and pension insurance.

The development of digital finance has expanded access to financial services, with a positive impact on household welfare [23,24]. Bank accounts are the basis for households' access to and use of financial services [25]. The use of bank accounts contributes to the improvement of households' financial situation [26,27] and increases productive investment and private expenditure [28]. Mobile payments expand the boundaries of households' social networks and enhance risk sharing and consumption smoothing [29–31]. Internet lending can ease financing constraints, enhance borrowing capacity, and promote household entrepreneurship [32–34]. Internet financial management can reduce investment costs, enhance household financial literacy, improve asset allocation, and help increase household property income [35].

Improved financial inclusion resulting from digital finance opens up new avenues for farm households to increase their income. In general, income from off-farm employment is usually much higher than income from farming, which weakens the social security function

of land [36–38], leading households to reconfigure factors of production and make the decision to move off farmland. Therefore, this study proposes the following hypothesis:

Hypothesis 1. *The use of digital finance can improve the probability and proportion of farmland transfer by rural households.*

2.2. Digital Finance and Off-Farm Employment

Digital finance has an off-farm employment effect, mainly in promoting entrepreneurship and increasing employed employment, which contributes to increasing rural household income.

Lack of initial capital is a major obstacle to farmers' entrepreneurship. Due to high costs, long physical distances, and lack of high-quality collateral assets, there are more serious information asymmetries between banks and their customers, making it difficult to manage lending risks [17]. Digital finance has clear advantages in overcoming information asymmetries and improving the efficiency of financial services [13,39]. Relying on the Internet and other information infrastructures, digital finance can reduce manual investment and dependence on physical business outlets, breakthrough time and space constraints, and realize the sinking of financial services [40]. Using the financial ecosystem of big technology platforms, digital finance can lower the marginal cost of financial services, enhance the extension and penetration of finance, and realize the long-tail effect. With the help of big data, cloud computing, artificial intelligence, and other cutting-edge financial technologies, digital finance can establish big data risk control models to accurately assess customer risks from the massive digital footprint, thereby effectively expanding credit supply and reducing default rate [41–43].

In addition, digital technology is an important driver of financial development. With the proliferation of information technology, there are differences in the absorptive capacity of different banks for new technologies, thus changing the competitive landscape of the banking industry [44–47]. Increased bank competition is conducive to improving the quality of financial services and promoting financial inclusion [48,49].

Consequently, the development of digital finance can alleviate financing constraints and provide credit funding support, thus providing more opportunities for household entrepreneurship [50].

While promoting entrepreneurship and booming local economies, digital finance can also stimulate labor demand for businesses and create more off-farm jobs, which can increase employed employment for rural households.

Both entrepreneurial business income and wage income from employed employment are generally higher than farm income [51,52]. Especially for small and medium-sized farmers, large-scale agricultural production has high inputs, long cycles, and high risks, while employed employment has the advantages of short cycles, high income, and stability, making the latter more attractive by comparison. Evidence from empirical studies shows that household income from off-farm employment is generally closely associated with lower land fragmentation [53]. Therefore, digital finance increases the opportunity cost of agricultural production for farmers, which will undoubtedly increase their propensity to transfer out of farmland. Based on the above analysis, this paper proposes hypothesis 2:

Hypothesis 2. *Digital finance can increase off-farm employment and promote farmland transfer-out.*

2.3. Digital Finance and Access to Information

Entering the digital society, information is a key social capital for households and is closely related to household livelihood strategies [54]. The development of ICT has facilitated the diffusion of information, weakened the barriers to household access to information, improved the quality of information, and positively impacted household welfare [55,56]. Digital finance has an information effect, and its reliance on the Internet

and digital media such as computers and mobile phones can improve farmers' access to information [57]. At present, China has not yet established a unified market for agricultural land transfer, the cost of searching for information on agricultural land transfer is high, it is difficult to match transactions, and the transfer contracts are not perfect, resulting in low efficiency of agricultural land transfer, and most of the transfer transactions take place between acquaintances, friends or relatives, and the transfer contracts have informal characteristics of being short-term and verbal [58]. With the help of digital technology, farmers can quickly and affordably access information on land transfer supply and demand, learn contracting and negotiation skills, and acquire the necessary contractual knowledge and dispute resolution skills, which will lower the transaction costs of land transfer and improve its efficiency [8].

In addition, the development of information technology, such as the Internet and mobile phones, has changed the way of education and provided learning channels for farmers [59]. Rich online learning resources help farmers to enhance their human capital. Participation in online interactions will enhance learning through word-of-mouth and observational learning [60–62]. Enhanced human capital helps households to improve their information processing capacity and make better land transfer decisions [63]. Therefore, hypothesis 3 is proposed.

Hypothesis 3. *Digital finance has an information effect, which will facilitate the transfer of agricultural land.*

Based on the above theoretical analysis, the theoretical framework of this study is shown in Figure 1.

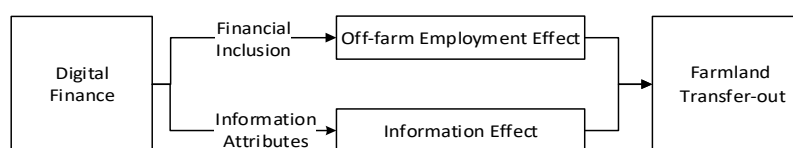


Figure 1. Theoretical framework.

3. Study Design

3.1. Data Sources

The China Household Finance Survey (CHFS), which was conducted nationally in 2015 by the China Household Finance Survey and Research Center of Southwest University of Finance and Economics, provided the data for the empirical analysis.

The sampling program of the China Household Finance Survey (CHFS) adopts a three-stage stratified sampling design. The primary sampling unit (PSU) is the 2585 cities/counties in the country excluding Tibet, Xinjiang, Inner Mongolia, Hong Kong, and Macao. The second-stage sampling will be conducted by sampling neighborhood/village councils directly from the cities/counties; and finally, households will be sampled from the neighborhood/village councils. Each stage of sampling is implemented using the PPS sampling method, which is weighted by the number of people (or households) in that sampling unit. The 2015 survey covers 29 provinces (autonomous regions and municipalities directly under the central government), 351 districts and counties, and 1396 villages (neighborhood) committees, with a sample size of 37,289 households, and the data are representative of the whole country, as well as of provincial and sub-provincial cities. The China Household Finance Survey collects information on household assets and liabilities, income and expenditure, insurance and protection, household demographic characteristics, and employment.

More importantly, the survey questionnaire in 2015 was designed with rich questions related to households' digital financial use and land transfer, providing data support for this paper's study (Up to now, the public has access to the survey data from 2011, 2013, 2015, 2017, and 2019; however, the surveys from 2017 and 2019 did not ask about a land transfer, and the surveys from 2011 and 2013 did not ask about digital finance). Since

agricultural land transfer involves rural households, this paper's study only retains the sample of households whose head is an agricultural household registration, and after deleting the missing values of relevant variables, a total of 11,802 valid household samples are obtained.

3.2. Model

Since the dependent variable in this study, land transfer, is a binary dummy variable, using OLS regression would violate the Gaussian Markov assumptions and lead to heteroskedasticity. Therefore, the Probit model is set up in this work to examine the effects of digital finance on household land transfer:

$$\text{Prob}(\text{Land} = 1) = \alpha + \beta Dfin + \gamma X + \mu \quad (1)$$

where *Land* denotes whether households transfer out their farmland management rights and take the value of 1 if they transfer out, and 0 otherwise; *Dfin* denotes whether they use digital finance (use = 1, no use = 0); *X* represents the control variable; μ is the random error term.

Since the land transfer proportion variable is truncated, linear regression of the entire sample using OLS leads to inconsistent estimates. Therefore, the following Tobit model is used in this paper to investigate the effect of digital finance on land transfer proportion:

$$LR^* = \alpha + \beta Dfin + \gamma X + \mu, LR = \max(0, LR^*) \quad (2)$$

where *LR* denotes land transfer proportion, *LR** denotes the observed value of land transfer proportion, and the rest of the variables are the same as in model (1).

3.3. Variables

3.3.1. Land Transfer and Land Transfer Proportion

Two explanatory variables, namely land transfer (whether transfer-out = 1, not transfer-out = 0) and land transfer proportion (the area of farmland transfer-out/household farmland area), are set in this paper to properly assess the farmland transfer-out behavior of households.

3.3.2. Digital Finance

Compared with the macro digital finance index at the regional level, the digital finance index constructed from the standpoint of digital finance product use based on micro survey data can reflect the penetration of digital finance in a more detailed and accurate way. Therefore, this paper refers to Song et al. (2020) to measure digital financial use in terms of payment and financial investment [24]. If households use online banking or mobile banking and invest in Internet wealth management, they are considered to participate in digital finance and are assigned a value of 1, otherwise, they are assigned a value of 0. In addition, this paper also uses digital financial intensity as a substitute for digital finance in the robustness test section.

3.3.3. Mechanism Variables

For the non-farm employment mechanism, the non-farm employment variable is generated based on the number of non-farm employment among household members. Two variables are included in the information channel mechanism: information use and information attention. Two variables are included in the information channel mechanism: information use and information attention. The former is generated based on whether households use smartphones to access information, and the latter is generated based on the degree to which households pay attention to financial and economic information, reflecting households' active access to information.

3.3.4. Control Variables

The control variables include age, gender, years of education, marital status of the household head, household size, financial literacy, whether or not the household has signed a land contract, whether or not the household has obtained a certificate of land contracting rights, the household off-farm assets and its disposable off-farm income, and control for provincial fixed effects. This paper conducted a two-sided 1% tail-shrinking treatment for continuous variables such as off-farm assets and disposable off-farm income to prevent the impact of extreme values on the regression findings. Table 1 displays specific variable definitions.

Table 1. Variable definitions.

Variable	Definitions
Land transfer	1 if households transfer out the contracted management right of farmland, otherwise 0
Land transfer proportion	The area of farmland transferred out to the area of household farmland
Digital Finance	1 if households use online banking, mobile banking, or Internet wealth management, otherwise 0
Digital financial intensity	The number of financial services used by households, including online banking, mobile banking, and Internet wealth management
Off-farm employment	the number of off-farm employed household members to the number of household members over 16 years old
Information use	1 if Households using smartphones to obtain information, otherwise 0
Information concern	Values are assigned according to the degree of concern for economic and financial information. Never concerned = 1, Seldomly concerned = 2, Generally concerned = 3, very concerned = 4, Extremely concerned = 5
Age	age of household head
Gender	1 if the head of the household is male, otherwise 0
Schooling	converted to 0, 6, 9, 12, 13, 15, 16, 19, and 22 years for no schooling, primary school, junior high school, senior high school, secondary school, college, undergraduate, master's, and doctoral degrees respectively
Marital status	1 if the head of the household is married, otherwise 0
Household size	The number of household members
Financial literacy	use factor analysis to build a measure of financial knowledge Three questions on interest rates, inflation, and investment risk were included in the 2015 CHFS questionnaire to assess the financial knowledge of household investors. This paper generates six dummy variables based on whether households answered these questions correctly and whether they answered them directly, and uses factor analysis to calculate the level of financial literacy of households.
Land contract	1 if households sign a land contract, otherwise 0
Land certificate	1 if the household has a certificate of land contracting rights, otherwise 0
Non-land assets	The logarithm of total non-land assets
Household income	The logarithm of household disposable off-farm income

The descriptive statistics for each variable are shown in Table 2. In the full sample, 18% of rural households transferred out of farmland management rights, and the mean land transfer proportion was 0.142, which was relatively low. Digital finance was used by 9.3% of rural households, and the mean value of digital financial intensity was 0.146, indicating that the penetration of digital finance was low in rural areas.

Table 2. Summary Statistics.

Variable	N	Mean	S.D.	Min	Max
Land transfer	11,802	0.180	0.384	0	1
Land transfer proportion	11,802	0.142	0.332	0	1
Digital Finance	11,802	0.093	0.290	0	1
Digital financial intensity	11,802	0.146	0.502	0	3
Off-farm employment	11,802	0.319	0.311	0	1
Information use	11,802	0.270	0.444	0	1
Information concern	11,777	1.900	1.051	1	5
Age	11,802	53.900	12.631	17	96
Gender	11,802	0.872	0.334	0	1
Marital status	11,802	0.896	0.306	0	1
Schooling	11,802	7.378	3.435	0	19
Household size	11,802	4.087	1.856	1	19
Financial literacy	11,802	−0.357	0.928	−1.340	1.097
Land contract	11,802	0.563	0.496	0	1
Land certificate	11,802	0.449	0.497	0	1
Non-land assets	11,802	11.886	1.369	7.972	15.217
Household income	11,802	10.051	1.524	2.398	12.764

Figure 2 displays scatter plots of household land transfer (left panel) and Land transfer proportion (right panel) along with digital finance, where digital finance, land transfer, and land transfer proportion are provincial-level means. Figure 2 shows that both land transfer and land transfer proportion have a stronger positive relationship with digital finance, which at first glance indicates that digital finance use has a positive impact on farmland transfer-out.

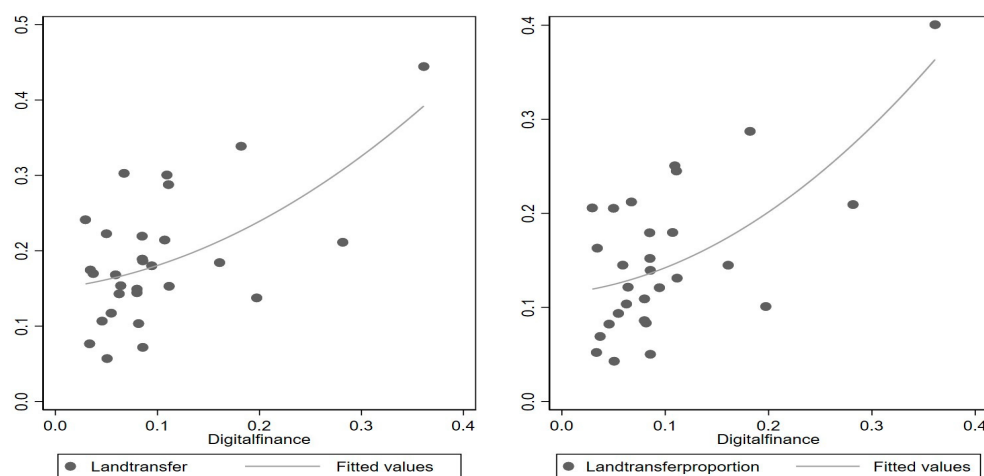


Figure 2. Scatterplot of digital finance and land transfer. Note: The vertical axis of the left panel is the participation of land transfer, and the vertical axis of the right panel is land transfer proportion; the horizontal axis is all digital finance indicators; the indicators are all averages at the provincial level.

4. Empirical Results

4.1. Baseline Regression

Table 3 reports the results of the benchmark regressions. Columns (1) and (2) examine the effect of digital finance on household participation in farmland transfers and are estimated using a Probit model, while columns (3) and (4) examine the effect on the proportion of farmland transfers and are estimated using a Tobit model. Columns (1) and (3) solely account for impacts that include province dummy variables and exclude other control variables. Control variables can be found in columns (2) and (4). The results show that digital finance significantly increases the probability of farmland transfer-out and the proportion of farmland transfer-out. As an example, the results in columns (2) and (4) show

that the use of digital finance by households was able to raise the probability of farmland transfer-out by 6.1% and the proportion of farmland transfer-out by 4.6%.

Table 3. Baseline Regression.

Variables	Land Transfer		Land Transfer Proportion	
	(1)	(2)	(3)	(4)
	Probit	Probit	Tobit	Tobit
Digital Finance	0.088 *** (0.011)	0.061 *** (0.012)	0.067 *** (0.009)	0.046 *** (0.011)
Age		0.002 *** (0.000)		0.002 *** (0.000)
Gender		−0.055 *** (0.010)		−0.045 *** (0.009)
Marital status		−0.042 *** (0.011)		−0.032 *** (0.009)
Schooling		0.005 *** (0.001)		0.004 *** (0.001)
Household size		−0.016 *** (0.002)		−0.014 *** (0.002)
Financial literacy		0.021 *** (0.004)		0.017 *** (0.003)
Land contract		0.037 *** (0.008)		0.029 *** (0.007)
Land certificate		−0.013 (0.008)		−0.011 * (0.007)
Non-land assets		0.011 *** (0.003)		0.011 *** (0.003)
Off-farm income		0.004 *** (0.001)		0.003 ** (0.001)
Province	yes	yes	yes	yes
N	11,802	11,802	11,802	11,802
Pseudo R ²	0.040	0.065	0.033	0.053

Note: *, **, *** represent significance at the 10%, 5%, and 1% levels respectively; Marginal effects are reported in the table and robust standard errors are in parentheses.

4.2. Endogeneity Discussion

The results of the baseline regression in Table 3 may have endogeneity issues due to reverse causality, omitted variables, and selection bias, which may lead to biased conclusions. In Table 4, instrumental variable regressions were carried out as a result. Specifically, this paper uses the mean value of digital financial use of other households in the city where they are located as an instrumental variable. On the one hand, the digital financial participation of farm households is influenced by the financial environment in which they live, and the higher the degree of digital financial development in the region, the higher the probability of using digital finance for farm households. On the other hand, it is difficult for individual households to have an impact on the overall level of digital finance in cities, and this paper excludes households' participation when calculating the overall level in cities, which further reduces the possibility of endogeneity existence.

Table 4. Instrumental variables.

Variables	(1)	(2)
	Ivprobit	Ivtobit
	Land Transfer	Land Transfer Proportion
Digital Finance	0.115 *** (0.028)	0.065 *** (0.015)
Control variable	yes	yes
Province	yes	yes
N	11,802	11,802
Instrumental variable coefficient		1.252 *** (0.222)
Atanhrho_12	−0.130 ** (0.063)	−0.080 ** (0.033)

Note: **, *** represent significance at the 5%, and 1% levels respectively; marginal effects are reported in the table and robust standard errors are in parentheses.

Since digital finance variables are discrete, this paper uses a Conditional Mixed Process approach for instrumental variables regression [64]. The results of the tests in Table 4 demonstrate that the coefficients of the instrumental variables in the first stage regression are significantly positive at the 1% level and there is no weak instrumental variable issue. The error term correlation coefficients (atanhrho_12) for the first and second stage regressions in the model with land transfer and land transfer proportion as dependent variables are −0.130 and −0.080, respectively, both significant at the 5% level, and the test results reject the original hypothesis that digital finance is an exogenous variable. The results of the above tests indicate that the use of instrumental variables is reasonable.

The regression results in Table 4 illustrate that after using instrumental variables to address endogeneity, digital finance increases the probability of farmland transfer-out by 11.5% and the proportion of farmland transfer-out by 6.5%, which are slightly larger than the outcomes of the baseline regression in Table 3, but do not change the significance level. Taken together, the outcomes of the instrumental variable regression in Table 4 and the baseline regression in Table 3 support Hypothesis 1.

4.3. Robustness Tests

First, this study narrows the sample to a rural sample. The previous baseline regression uses a sample of households whose head has an agricultural household registration. There may be some households that still retain an agricultural household registration but have settled in urban areas and do not live in rural areas. To capture the impact of digital finance on land transfer for rural households that have not yet migrated to urban areas, this paper re-runs the regression using the rural area sample, and the regression results are reported in column (1) of Table 5. The results show that digital finance has a significant positive effect on the probability of transferring farmland at the 5% level, which is generally consistent with the findings of the benchmark regression.

Second, this study excludes the sample of those who transferred out farmland due to declining labor capacity. With the increase of aging, farmers' labor ability tends to decline. Therefore, transferring out farmland becomes a passive choice for this group of farmers. To exclude the land transfer behavior due to declining labor capacity, this paper restricts farmers to those under 70 years old, and the regression results based on such sample data are listed in column (2) of Table 5. The findings indicate that there is still a considerable impact of digital banking on farmland transfer-out.

Third, this paper redefines digital financial variables based on the types of digital financial use. Specifically, digital financial intensity is generated by assigning values according to the number of types of digital financial services such as online banking, mobile banking, and internet wealth management used by households. The more types of digital financial services are used, the higher the intensity of use. The results in column (3) of

Table 5 show that the marginal effect of digital financial use intensity on household land transfer is 0.028 and is significant at the 1% level.

Table 5. Robustness test.

Variables	(1)	(2)	(3)	(4)
	Rural Sample	The Sample under 70 Years Old	Digital Financial Intensity	New Land Transfers
Digital Finance	0.040 ** (0.017)	0.051 *** (0.012)	0.028 *** (0.007)	0.049 *** (0.017)
Control variable	yes	yes	yes	yes
Province	yes	yes	yes	yes
N	7599	10,501	11,802	5244
Pseudo R ²	0.079	0.064	0.064	0.054

Note: **, *** represent significance at the 5%, and 1% levels respectively; Marginal effects are reported in the table and robust standard errors are in parentheses.

Finally, this study substitutes for the dependent variable. It is possible that households had already experienced land transfers before using digital finance, and the cross-sectional data in this paper do not reflect this change. For this reason, this paper matches the two CHFS surveys in 2013 and 2015, excludes households that had already transferred out of farmland at the time of the 2013 survey, and uses a follow-up sample of respondents from both surveys to investigate the impact of digital finance use on households' new farmland transfers. The regression results presented in column (4) of Table 5 shows that digital finance use has a significant contribution to households' new farmland transfers, supporting the baseline regression results.

4.4. Further Discussion

4.4.1. Heterogeneity Analysis

Despite the potential of digital finance to realize inclusive growth, there are also concerns that the development of digital finance will exacerbate inequality [13,65]. Digital finance is based on the use of digital technology, yet the ability to use digital technology varies across individuals [66]. Do the digital skills divide hinder decisions on agricultural land transfer? This study analyses this. In general, older people, low-income groups, and individuals with disabilities are more vulnerable to financial exclusion and face a greater digital divide [67,68]. For this purpose, this study runs separate group regressions by age of household head, per capita income, and financial accessibility. The regression findings are presented in Table 6.

Table 6. Heterogeneity analysis.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	Older Group	Younger Group	High-Income Group	Low-Income Group	High Financial Accessibility Group	Low Financial Accessibility Group
Digital finance	0.078 *** (0.025)	0.041 *** (0.015)	0.049 *** (0.016)	0.084 *** (0.023)	0.050 *** (0.016)	0.069 *** (0.023)
Control variable	yes	yes	yes	yes	yes	yes
Province	yes	yes	yes	yes	yes	yes
N	6186	5616	5901	5901	5912	5890
Pseudo R ²	0.074	0.072	0.061	0.083	0.066	0.064

Note: *** represent significance at the 1% levels respectively; Marginal effects are reported in the table and robust standard errors are in parentheses.

First, the sample is divided into an older group (median and above) and a younger group (below the median) according to the median age of the household head. The results in columns (1) and (2) of Table 6 demonstrate that the marginal effect of digital finance on farmland transfer is almost twice as large in the older group as in the younger group,

indicating that digital finance has a greater effect on the transfer-out of farmland from households with older heads.

Second, based on household per capita income, the sample is split into two income groups: high income (median and above) and low income (below median), and columns (3) and (4) of Table 6 detail the marginal impacts of the regressions. The results show that the marginal effect of digital finance use on farmland transfer is 0.084 in the low-income group, much higher than 0.049 in the high-income group, demonstrating that digital finance has a greater impact on land transfer for rural households with low per capita income.

Finally, the average number of bank accounts of households at the village level was calculated, and households were considered to have good financial accessibility if the average number of accounts was greater than or equal to the median, and were assigned a value of 1, otherwise, they were assigned a value of 0. Accordingly, the sample was split into two groups: one with great financial accessibility and the other with low financial accessibility. The regression results in columns (5) and (6) of Table 6 shows that digital finance has a more significant effect on the transfer of farmland by households in the low financial accessibility group, with a marginal effect of 0.069, larger than that of 0.050 in the high financial accessibility group. Digital finance is less dependent on physical business outlets and has a spatial and temporal advantage in financial services, which will significantly reduce financial transaction costs and enhance the accessibility of financial services, thus driving land transfer.

Overall, the results of the heterogeneity analysis in Table 6 show that digital finance has a greater effect on the transfer of land from rural households with older heads of household and lower per capita income and financial accessibility. This demonstrates the important role of digital finance in reducing inequality and achieving inclusive growth.

4.4.2. Mechanism Analysis

Digital Finance and Off-Farm Employment

Theoretically, off-farm work increases the opportunity cost of farming activities and weakens the social security function of farmland, which in turn prompts households to decide to move out of their farmland holdings. As a result, off-farm employment may be one of the mediating mechanisms through which digital finance affects households' farmland transfers. Based on the primary jobs held by household members, this paper generates off-farm employment variables, i.e., the share of off-farm employment among household members. Overall, in 2015, the average share of off-farm employment among the sample households was 31.89%, of which 8.29% of household members had formal employment contracts and were employed by others or units; 17.50% of household members did not have formal employment contracts and were engaged in temporary jobs such as odd jobs; 5.37% of household members ran their businesses and were self-employed; 0.74% of household members were engaged in other types of work such as freelance work.

Column (1) of Table 7 performs an OLS regression with the off-farm employment proportion as the dependent variable. The results show that digital finance has a significant positive impact on off-farm employment, with a marginal effect of 0.094 for the digital finance variable. Similar results from the regression employing instrumental variables are shown in column (2) of Table 7, indicating that digital finance promotes off-farm employment. To evaluate the effects of digital finance on various types of off-farm employment, columns (3)–(5) of Table 7 further distinguish off-farm employment into three types: employed by someone or some units (referred to as employee), temporary jobs, and entrepreneurship. The findings demonstrate that digital finance significantly promotes employed employment and household entrepreneurship, reduces temporary employment, and has a larger effect on employees than household entrepreneurship, with marginal effects of 0.105 and 0.039, respectively. The growth of digital finance can improve the protection of rural residents' rights and interests in the labor market and promote off-farm

employment, as evidenced by its suppressive effect on temporary employment without a formal employment contract.

Table 7. Off-farm employment.

Variables	(1)	(2)	(3)	(4)	(5)
	OLS	2SLS	OLS	OLS	OLS
	Off-Farm Employment	Off-Farm Employment	Employee	Temporary Jobs	Entrepreneurship
Digital Finance	0.094 *** (0.010)	1.187 *** (0.134)	0.105 *** (0.009)	−0.053 *** (0.009)	0.039 *** (0.008)
Control variable	yes	yes	yes	yes	yes
Province	yes	yes	yes	yes	yes
N	11,802	11,802	11,802	11,802	11,802
R ²	0.241	–	0.155	0.062	0.128

Note: *** represent significance at the 1% levels respectively; Robust standard errors are in parentheses.

The results in Table 7 show that digital finance promotes off-farm employment among farm households, so a further question is, in what industries do farmers engage in off-farm employment? Which skill types of farmers' employment will be affected by digital finance? This study analyzed this using individual data from the 2015 CHFS survey and the results are presented in Table 8.

Table 8. Off-farm Employment Industry and Skill Heterogeneity.

Variables	(1)	(2)	(3)	(4)	(5)
	Probit	Probit	Probit	Probit	Probit
	Secondary Sector Employment	Tertiary Sector Employment	Low-Skilled Farmers	Medium-Skilled Farmers	Highly Skilled Farmers
Digital Finance	−0.070 *** (0.022)	0.062 *** (0.021)	0.086 *** (0.021)	0.070 *** (0.013)	0.030 (0.019)
Control variable	yes	yes	yes	yes	yes
Province	yes	yes	yes	yes	yes
N	3700	3700	7066	12,601	1258
Pseudo R ²	0.093	0.095	0.176	0.239	0.123

Note: *** represent significance at the 1% levels respectively; Marginal effects are reported in the table and robust standard errors are in parentheses; Smaller samples in columns (1) and (2) are due to the higher number of missing.

First, columns (1) and (2) of Table 8 generate two dependent variables, secondary sector employment (respondents employed in the secondary sector = 1, otherwise 0) and tertiary sector employment (respondents employed in the tertiary sector = 1, otherwise = 0), respectively, where the secondary sector comprises the mining sector, the manufacturing sector, the electric power, heat, gas, and water production and supply sector, and the construction sector. The tertiary sector mainly includes service sectors such as wholesale and retail, transportation, finance, real estate, information transmission, software, and information technology services. The results show that the marginal effect in column (1) is −0.070 and the marginal effect in column (2) is 0.062, both of which are significant at the 1% level. This suggests that digital finance reduces the probability of farmers being employed in the secondary industry and increases the probability of being employed in the tertiary industry, which is consistent with the reality that the tertiary industry has been booming in China in recent years. Digital finance has driven the digitization of the tertiary industry, and new service industry formats such as takeaways, live streaming with goods, and online car rental have attracted a large number of groups to employment.

Second, this study removes school students and retains adult farmers aged between 16 and 60 years old, and categorizes them into three groups according to their educational qualifications: low-skill farmers (with less than a junior high school education), middle-skill

farmers (with a junior high school education and above, and less than a college education), and high-skill farmers (with a college education and above). The impact of digital finance on off-farm employment of farmers with different skills is examined through Probit modeling. The results in columns (3), (4), and (5) of Table 8 shows that digital finance significantly contributes to the off-farm employment of low-skilled and middle-skilled farmers and has no effect on the off-farm employment of high-skilled farmers. This may be because high-skilled farmers have higher educational levels and therefore can achieve off-farm employment even without digital finance. This result further confirms that digital finance does not exacerbate inequality and can benefit low and middle-skilled groups.

Overall, the results in Tables 7 and 8 confirm the existence of the off-farm employment mechanism in Hypothesis 2.

Digital Finance and Information Channel

To verify the information channel mechanism, this paper sets up two proxy variables, information use, and information concern. First, the information use variable is generated based on whether households use mobile phones to access information. If use is assigned a value of 1, otherwise 0. The regression results are presented in columns (1) and (2) of Table 9. Second, the information concern variable is generated based on the degree of concern of households about financial and economic information. The higher the level of attention, the larger the value. The information attention variable reflects, in part, the active learning effect of households on information. Since the degree of information concern is discrete and ordered, this study uses the Oprobit model for the regression and the results are presented in columns (3) and (4) of Table 9.

Table 9. Information Channel.

Variables	(1)	(2)	(3)	(4)
	Probit	IvProbit	Oprobit	IvOprobit
	Information Use	Information Use	Information Concern	Information Concern
Digital Finance	0.184 *** (0.012)	0.164 *** (0.051)	0.210 *** (0.035)	0.724 *** (0.260)
Control variable	yes	yes	yes	yes
Province	yes	yes	yes	yes
N	11,802	11,802	11,777	11,777
Pseudo R ²	0.264	-	0.050	

Note: *** represent significance at the 1% levels respectively; Robust standard errors are in parentheses; The sample reduction in columns (3) and (4) is due to missing samples for the information concern variable.

The results of the Probit regression with information use as the dependent variable in column (1) of Table 9 show that the digital finance variable is significantly positive at the 1% level. The regression results using instrumental variables in column (2) of Table 9 similarly indicate that the use of digital finance will lead to an increase in the probability that a farmer will use a mobile phone to access information by 16.4 percent. Columns (3) and (4) of Table 9 present the results of the regressions with information concern as the dependent variable. The results in column (3) show that digital finance helps farmers increase their concern for economic and financial information. The regression in column (4) based on instrumental variables similarly supports these findings.

Overall, the regression results in Table 9 confirm that the information channel mechanism proposed in Hypothesis 3 does exist.

5. Conclusions and Implications

Based on the 2015 China Household Finance Survey (CHFS) data, this paper empirically analyzes the effects and mechanisms of digital finance on household farmland transfers. The findings show that digital finance significantly increases the probability and

proportion of farmland transfer out for rural households, and this positive effect is more pronounced among rural households with older household heads and lower per capita income and financial accessibility, indicating that digital finance has an important role to play in reducing inequality and promoting inclusive growth. Off-farm employment and information channels are mediating mechanisms for digital finance to facilitate farmland transfer. Further studies of off-farm employment demonstrate that digital finance increases employed employment and entrepreneurship and decreases temporary employment among rural households. Specifically, on the one hand, the financial function of digital finance increases the share of employment and entrepreneurship among rural households. In terms of industry and skill type, digital finance promotes the entry of farmers into tertiary employment, facilitates off-farm employment for low and medium-skilled farmers, and has no impact on the employment of high-skilled farmers. On the other hand, the information function accompanying digital finance broadens households' access to information, both of which have a favorable effect on farmland transfer-out.

The findings of this study contribute to an in-depth understanding of the intrinsic relationship between the use of digital finance and farmland transfer and have important policy implications for improving the efficiency of farmland management and expanding the marketability of farmland markets. To give full play to the support effect of digital finance on farmland transfer, the following recommendations are made:

First, we should accelerate the construction of the "digital countryside" and improve the foundation for digital financial development. Compared with urban areas, information infrastructure construction in rural areas of China is relatively weak. Government departments should increase financial investment to improve the Internet penetration rate in rural areas and continuously explore the digital application of rural industrial operations.

Second, popularize digital finance education and improve the digital financial literacy of rural residents. A high level of digital financial literacy helps rural households access financial information and use financial services, thus optimizing households' financial decisions and promoting income growth. The digital financial literacy of China's rural residents is inherently low, and the aging and hollowing out of the rural population due to urbanization further exacerbates the issue. It is the responsibility of the government as well as various rural financial institutions to increase investment in financial education and adopt various forms to popularize digital financial literacy in the context of rural production and business scenarios. For special groups such as the rural elderly, digital financial APPs such as the rural version and the elderly-friendly version have been developed to simplify the operating interface and reduce the difficulty of operation. At the same time, manual, remote, and door-to-door services for rural elderly groups have been strengthened to improve the convenience of financial services for elderly groups. Training in digital financial knowledge and skills for the elderly has been increased, guiding the elderly to actively integrate into digital life, improving their ability to use digital financial products and services to improve their own lives, and gradually eliminating the digital divide and financial exclusion.

Third, rural financial institutions need to accelerate digital transformation and increase the supply of digital financial services. By introducing and absorbing emerging technologies such as big data and artificial intelligence, they can optimize the risk control model and effectively control credit risks. Combined with the characteristics of rural financial businesses, the digital transformation of outlets is carried out to reduce the cost of financial services. Based on stabilizing traditional advantageous products and accelerating financial innovation, rural financial institutions actively explore digital financial products that fit rural production and business scenarios.

Finally, it is necessary to promote the digitalization of the tertiary industry and actively use digital technology to cultivate new forms and modes of service industries, thereby creating more demand for services and giving full play to the employment function of the tertiary industry. Government departments need to break down barriers to the employment

of farmers and create a favorable employment environment, thereby promoting the off-farm employment of farmers.

Due to data limitations, the digital finance indicators in this study include only three categories: mobile banking, online banking, and Internet wealth management. The connotation of digital finance is much more than that, and more digital finance content can be included in the future to measure digital finance indicators more precisely. In addition, the impact of digital finance on other areas, such as farmland management, farmland rent, and employment of farm households, could be further explored in the future.

Author Contributions: Conceptualization, H.L. and Q.S.; Methodology, H.L. and Q.S.; Investigation, H.L. and Q.S.; Writing—original draft, H.L.; Writing—review & editing, H.L. and Q.S.; Visualization, H.L.; Supervision, H.L. and Q.S.; Funding acquisition, H.L. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data presented in this study are openly available based on official rules in Survey and Research Center for China Household Finance at <https://chfser.swufe.edu.cn/datasso/Home/Login?5569928325197862210> (accessed on 31 July 2019).

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Lipton, M.; Saghai, Y. Food security, farmland access ethics, and land reform. *Glob. Food Secur.* **2017**, *12*, 59–66. [\[CrossRef\]](#)
2. Han, H.; Li, H.; Zhao, L. Determinants of Factor Misallocation in Agricultural Production and Implications for Agricultural Supply-side Reform in China. *China World Econ.* **2018**, *26*, 22–42. [\[CrossRef\]](#)
3. Kuang, Y.-P.; Yang, J.-L.; Abate, M.-C. Farmland transfer and agricultural economic growth nexus in China: Agricultural TFP intermediary effect perspective. *China Agric. Econ. Rev.* **2022**, *14*, 184–201. [\[CrossRef\]](#)
4. Fei, R.; Lin, Z.; Chunga, J. How land transfer affects agricultural land use efficiency: Evidence from China's agricultural sector. *Land Use Policy* **2021**, *103*, 105300. [\[CrossRef\]](#)
5. Deng, X.; Xu, D.; Zeng, M.; Qi, Y. Does early-life famine experience impact rural land transfer? Evidence from China. *Land Use Policy* **2019**, *81*, 58–67. [\[CrossRef\]](#)
6. 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. [\[CrossRef\]](#)
7. Huang, K.; Cao, S.; Qing, C.; Xu, D.; Liu, S. Does labour migration necessarily promote farmers' land transfer-in?—Empirical evidence from China's rural panel data. *J. Rural Stud.* **2023**, *97*, 534–549. [\[CrossRef\]](#)
8. Zou, B.; Mishra, A.K. How internet use affects the farmland rental market: An empirical study from rural China. *Comput. Electron. Agric.* **2022**, *198*, 107075. [\[CrossRef\]](#)
9. Liu, Y.; Heerink, N.; Li, F.; Shi, X. Do agricultural machinery services promote village farmland rental markets? Theory and evidence from a case study in the North China plain. *Land Use Policy* **2022**, *122*, 106388. [\[CrossRef\]](#)
10. Gao, X.; Shi, X.; Fang, S. Property rights and misallocation: Evidence from land certification in China. *World Dev.* **2021**, *147*, 105632. [\[CrossRef\]](#)
11. Pazarbasioglu, C.; Mora, A.G.; Uttamchandani, M.; Natarajan, H.; Feyen, E.; Saal, M. *Digital Financial Services*; World Bank: Washington, DC, USA, 2020; Volume 54.
12. Jiang, S.; Qiu, S.; Zhou, H. Will digital financial development affect the effectiveness of monetary policy in emerging market countries? *Econ. Res. -Ekon. Istraživanja* **2022**, *35*, 3437–3472. [\[CrossRef\]](#)
13. Ozili, P.K. Impact of digital finance on financial inclusion and stability. *Borsa Istanbul. Rev.* **2018**, *18*, 329–340. [\[CrossRef\]](#)
14. Ahmad, M.; Majeed, A.A.; Khan, M.A.; Sohaib, M.; Shehzad, K. Digital financial inclusion and economic growth: Provincial data analysis of China. *China Econ. J.* **2021**, *14*, 291–310. [\[CrossRef\]](#)
15. Xie, S.; Jin, C.; Song, T.; Feng, C. Research on the long tail mechanism of digital finance alleviating the relative poverty of rural households. *PLoS ONE* **2023**, *18*, e0284988. [\[CrossRef\]](#)
16. Adams, D.W.; Nehman, G.I. Borrowing costs and the demand for rural credit. *J. Dev. Stud.* **1979**, *15*, 165–176. [\[CrossRef\]](#)
17. Demirgüç-Kunt, A.; Klapper, L.F. Measuring Financial Inclusion: The Global Findex Database. World Bank Policy Research Working Paper. 2012. Available online: <https://ssrn.com/abstract=2043012> (accessed on 18 July 2023).
18. Jack, W.; Suri, T. Risk Sharing and Transactions Costs: Evidence from Kenya's Mobile Money Revolution. *Am. Econ. Rev.* **2014**, *104*, 183–223. [\[CrossRef\]](#)

19. Yu, X.; Su, Q.; Lyu, J. Does access to credit matter in land transfer decision-making? Evidence from China. *Front. Environ. Sci.* **2023**, *11*, 226. [CrossRef]
20. Li, C.; Ma, W.; Mishra, A.K.; Gao, L. Access to credit and farmland rental market participation: Evidence from rural China. *China Econ. Rev.* **2020**, *63*, 101523. [CrossRef]
21. Wang, X.; Weaver, N.; You, J. The Social Security Function of Agriculture in China. *J. Int. Dev.* **2013**, *25*, 1–10. [CrossRef]
22. Wang, Y.; Li, X.; He, H.; Xin, L.; Tan, M. How reliable are cultivated land assets as social security for Chinese farmers? *Land Use Policy* **2020**, *90*, 104318. [CrossRef]
23. Yang, T.; Zhang, X. FinTech adoption and financial inclusion: Evidence from household consumption in China. *J. Bank. Financ.* **2022**, *145*, 106668. [CrossRef]
24. Song, Q.; Li, J.; Wu, Y.; Yin, Z. Accessibility of financial services and household consumption in China: Evidence from micro data. *N. Am. J. Econ. Financ.* **2020**, *53*, 101213. [CrossRef]
25. Allen, F.; Demircuc-Kunt, A.; Klapper, L.; Martinez Peria, M.S. The foundations of financial inclusion: Understanding ownership and use of formal accounts. *J. Financ. Intermediat.* **2016**, *27*, 1–30. [CrossRef]
26. Prina, S. Banking the poor via savings accounts: Evidence from a field experiment. *J. Dev. Econ.* **2015**, *115*, 16–31. [CrossRef]
27. Rhine, S.L.; Greene, W.H.; Toussaint-Comeau, M. The importance of check-cashing businesses to the unbanked: Racial/ethnic differences. *Rev. Econ. Stat.* **2006**, *88*, 146–157. [CrossRef]
28. Dupas, P.; Robinson, J. Savings Constraints and Microenterprise Development: Evidence from a Field Experiment in Kenya. *Am. Econ. J. Appl. Econ.* **2013**, *5*, 163–192. [CrossRef]
29. Abor, J.Y.; Amidu, M.; Issahaku, H. Mobile Telephony, Financial Inclusion and Inclusive Growth. *J. Afr. Bus.* **2018**, *19*, 430–453. [CrossRef]
30. Riley, E. Mobile money and risk sharing against village shocks. *J. Dev. Econ.* **2018**, *135*, 43–58. [CrossRef]
31. Tabetando, R.; Matsumoto, T. Mobile money, risk sharing, and educational investment: Panel evidence from rural Uganda. *Rev. Dev. Econ.* **2020**, *24*, 84–105. [CrossRef]
32. Jagtiani, J.; Lemieux, C. Do fintech lenders penetrate areas that are underserved by traditional banks? *J. Econ. Bus.* **2018**, *100*, 43–54. [CrossRef]
33. Cornelli, G.; Frost, J.; Gambacorta, L.; Rau, P.R.; Wardrop, R.; Ziegler, T. Fintech and big tech credit: Drivers of the growth of digital lending. *J. Bank. Financ.* **2023**, *148*, 106742. [CrossRef]
34. Ye, B.; Yuan, J.; Guan, Y. Internet Finance, Financing of Small and Micro Enterprises and the Macroeconomy. *Emerg. Mark. Financ. Trade* **2022**, *58*, 2851–2866. [CrossRef]
35. Guo, C.; Wang, X.; Yuan, G. Digital Finance and the Efficiency of Household Investment Portfolios. *Emerg. Mark. Financ. Trade* **2022**, *58*, 2895–2909. [CrossRef]
36. Peng, K.; Yang, C.; Chen, Y. Land transfer in rural China: Incentives, influencing factors and income effects. *Appl. Econ.* **2020**, *52*, 5477–5490. [CrossRef]
37. Xu, D.; Deng, X.; Guo, S.; Liu, S. Labor migration and farmland abandonment in rural China: Empirical results and policy implications. *J. Environ. Manag.* **2019**, *232*, 738–750. [CrossRef]
38. Mishra, A.K.; Fannin, J.M.; Joo, H. Off-Farm Work, Intensity of Government Payments, and Farm Exits: Evidence from a National Survey in the United States. *Can. J. Agric. Econ./Rev. Can. D'agroekon.* **2014**, *62*, 283–306. [CrossRef]
39. Bachas, P.; Gertler, P.; Higgins, S.; Seira, E. Digital Financial Services Go a Long Way: Transaction Costs and Financial Inclusion. *AEA Pap. Proc.* **2018**, *108*, 444–448. [CrossRef]
40. Deng, J.; Liu, Y. Does digital finance reduce the employment in the finance industry? Evidence from China. *Financ. Res. Lett.* **2022**, *48*, 102994. [CrossRef]
41. Berg, T.; Burg, V.; Gombović, A.; Puri, M. On the Rise of FinTechs: Credit Scoring Using Digital Footprints. *Rev. Financ. Stud.* **2020**, *33*, 2845–2897. [CrossRef]
42. Agarwal, S.; Alok, S.; Ghosh, P.; Gupta, S. Financial Inclusion and Alternate Credit Scoring for the Millennials: Role of Big Data and Machine Learning in Fintech. In *Business School, National University of Singapore Working Paper*; SSRN: Amsterdam, The Netherlands, 2020; p. 3507827.
43. Huang, Y.; Zhang, L.; Li, Z.; Qiu, H.; Sun, T.; Wang, X. Fintech Credit Risk Assessment for SMEs: Evidence from China. IMF Working Papers. 2020. Available online: <https://ssrn.com/abstract=3721218> (accessed on 16 July 2023).
44. Berger, A.N. The Economic Effects of Technological Progress: Evidence from the Banking Industry. *J. Money Credit Bank.* **2003**, *35*, 141–176. [CrossRef]
45. Hauswald, R.; Marquez, R. Information Technology and Financial Services Competition. *Rev. Financ. Stud.* **2003**, *16*, 921–948. [CrossRef]
46. Thakor, A.V. Fintech and banking: What do we know? *J. Financ. Intermediat.* **2020**, *41*, 100833. [CrossRef]
47. Bejar, P.; Ishi, K.; Komatsuzaki, T.; Shibata, I.; Sin, J.; Tambunlertchai, S. Can Fintech Foster Competition in the Banking System in Latin America and the Caribbean? *Lat. Am. J. Cent. Bank.* **2022**, *3*, 100061. [CrossRef]
48. Pham, T.T.T.; Nguyen, T.V.H.; Nguyen, K. Does bank competition promote financial inclusion? A cross-country evidence. *Appl. Econ. Lett.* **2019**, *26*, 1133–1137. [CrossRef]
49. Jame, R.; Markov, S.; Wolfe, M.C. Can FinTech Competition Improve Sell-Side Research Quality? *Account. Rev.* **2022**, *97*, 287–316. [CrossRef]

50. Liu, S.; Koster, S.; Chen, X. Digital divide or dividend? The impact of digital finance on the migrants' entrepreneurship in less developed regions of China. *Cities* **2022**, *131*, 103896. [\[CrossRef\]](#)
51. Imai, K.S.; Gaiha, R.; Thapa, G. Does non-farm sector employment reduce rural poverty and vulnerability? Evidence from Vietnam and India. *J. Asian Econ.* **2015**, *36*, 47–61. [\[CrossRef\]](#)
52. Ba, M.; Anwar, A.; Mughal, M. Non-farm employment and poverty reduction in Mauritania. *J. Int. Dev.* **2021**, *33*, 490–514. [\[CrossRef\]](#)
53. Tan, S.; Heerink, N.; Qu, F. Land fragmentation and its driving forces in China. *Land Use Policy* **2006**, *23*, 272–285. [\[CrossRef\]](#)
54. Baird, T.D.; Hartter, J. Livelihood diversification, mobile phones and information diversity in Northern Tanzania. *Land Use Policy* **2017**, *67*, 460–471. [\[CrossRef\]](#)
55. Leng, C.; Ma, W.; Tang, J.; Zhu, Z. ICT adoption and income diversification among rural households in China. *Appl. Econ.* **2020**, *52*, 3614–3628. [\[CrossRef\]](#)
56. Zhu, Q.; Zhu, C.; Peng, C.; Bai, J. Can information and communication technologies boost rural households' income and narrow the rural income disparity in China? *China Econ. Q. Int.* **2022**, *2*, 202–214. [\[CrossRef\]](#)
57. Yang, X.; Huang, Y.; Gao, M. Can digital financial inclusion promote female entrepreneurship? Evidence and mechanisms. *N. Am. J. Econ. Financ.* **2022**, *63*, 101800. [\[CrossRef\]](#)
58. Xie, Y.; Jiang, Q. Land arrangements for rural–urban migrant workers in China: Findings from Jiangsu Province. *Land Use Policy* **2016**, *50*, 262–267. [\[CrossRef\]](#)
59. Korkmaz, Ö.; Erer, E.; Erer, D. Internet access and its role on educational inequality during the COVID-19 pandemic. *Telecommun. Policy* **2022**, *46*, 102353. [\[CrossRef\]](#)
60. Liang, P.; Guo, S. Social interaction, Internet access and stock market participation—An empirical study in China. *J. Comp. Econ.* **2015**, *43*, 883–901. [\[CrossRef\]](#)
61. Hong, H.; Stein, J.C. Disagreement and the Stock Market. *J. Econ. Perspect.* **2007**, *21*, 109–128. [\[CrossRef\]](#)
62. Sconti, A. Digital vs. in-person financial education: What works best for Generation Z? *J. Econ. Behav. Organ.* **2022**, *194*, 300–318. [\[CrossRef\]](#)
63. Jiang, M.; Li, J.; Paudel, K.P.; Mi, Y. Factors affecting agricultural land transfer-out in China: A semiparametric instrumental variable model. *Appl. Econ. Lett.* **2019**, *26*, 1729–1733. [\[CrossRef\]](#)
64. Roodman, D. Fitting fully observed recursive mixed-process models with cmp. *Stata J.* **2011**, *11*, 17. [\[CrossRef\]](#)
65. Yue, P.; Korkmaz, A.G.; Yin, Z.; Zhou, H. The rise of digital finance: Financial inclusion or debt trap? *Financ. Res. Lett.* **2022**, *47*, 102604. [\[CrossRef\]](#)
66. van Deursen, A.J.A.M.; van Dijk, J.A.G.M. The digital divide shifts to differences in usage. *New Media Soc.* **2013**, *16*, 507–526. [\[CrossRef\]](#)
67. Rhine, S.L.W.; Greene, W.H. The Determinants of Being Unbanked for U.S. Immigrants. *J. Consum. Aff.* **2006**, *40*, 21–40. [\[CrossRef\]](#)
68. van Deursen, A.J.A.M.; van Dijk, J.A.G.M.; Peters, O. Rethinking Internet skills: The contribution of gender, age, education, Internet experience, and hours online to medium- and content-related Internet skills. *Poetics* **2011**, *39*, 125–144. [\[CrossRef\]](#)

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.