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Can Digital Finance Promote Professional Farmers' Income Growth in China?—An Examination Based on the Perspective of Income Structure

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Abstract: As a product of the deep integration of digital technology and financial services, digital finance provides vital financial support for rural revitalization and increasing farmers' income. Based on the survey data of 1030 professional apple growers in the typical areas of Shaanxi Province, this paper empirically tested the impact of digital financial involvement on professional farmers' income, and its mechanism. The study found that digital finance significantly impacted the growth of professional farmer households' total incomes. However, this impact was not achieved by directly increasing property income and transfer incomes, but through two indirect ways: first, digital finance promoted productive agricultural investment, which further promoted the increase in agricultural income; secondly, digital finance further increased the income of self-operated industry and commerce by promoting the entrepreneurship of professional farmer households. Furthermore, the heterogeneity analysis showed that professional farmers with high education levels, large-scale farmland operations, and high levels of agricultural mechanization participate in digital finance, which plated a more significant role in promoting their total household income. From the perspective of different types of digital financial services, mobile payment and digital credit could promote increases in the income of professional farmers, but the income increase effect of digital wealth management has not yet been shown.

Keywords: digital finance; professional farmers' income; income structure

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1. Introduction

Increasing farmers' income has always been the focus of "agriculture, rural areas, and farmers". In February 2023, the Central Committee of the Communist Party of China and the State Council issued the "Opinions on Doing a Good Job in the Key Tasks of Comprehensively Promoting Rural Revitalization in 2023", emphasizing that it is necessary to ensure stable and increased agricultural production, farmers' income, and rural stability and tranquility. Finance has significantly increased farmers' income as the core of resource allocation in the modern rural economy [1]. However, due to actual institutional and institutional reasons, there are still some disadvantages that are difficult to overcome in the process of supporting rural revitalization, such as narrow channels, high costs, and lack of innovation, which restrict the quality and effectiveness of financial services [2]. With the continuous integration of digital technology and the financial field in recent years, digital finance has emerged as the times require. Compared with traditional finance, the advantages of digital finance are, first, with the help of digital technology, the "soft information" of farmers' online payment, shopping, social networking, and financial management can be digitized and coded into "hard information" for testing farmers' credit. This helps to alleviate information asymmetry when lending. Second, relying on its technical advantages in information transmission, reception, analysis, and processing, it reduces transaction costs and broadens the possibility boundary of transactions [2,3].

Digital finance is a potentially transformative model for expanding financial supply and realizing financial inclusion, bringing new solutions to serve rural revitalization, increase farmers' income and promote rural prosperity. In this context, exploring the relationship between digital finance and farmers' income will help to deepen our understanding of the income-increasing effect of digital finance on the one hand, and provide empirical evidence for rural revitalization decision-making departments on the other hand.

Presently, studies on the relationship between digital finance and farmers' income mainly focus on three aspects: First of all, the impact of digital finance on income levels. Yin et al. [4] found that digital finance did not significantly impact income. Wang et al. [5] believe that digital finance has no significant impact on the income increase of poor households, but has a more significant effect on the income increase of non-poor households. However, Zhang et al. [6] argued that digital finance plays a significant role in promoting the growth of farmers' income, and the poor benefit more from it than the rich. Although the existing research conclusions are still controversial, the academic community generally positively affirms the income-increasing effect of digital finance [7–10]. In addition, studies from Kenya [11] and Uganda [12] also reached similar conclusions. Secondly, the impact of digital finance on the income structure is also an area of concern. One approach is based on the analysis of macrodata. Zhang [13] found that digital finance could significantly promote wages, agricultural operations, property, and transfer income. Liu et al. [14] showed that digital finance could positively impact wage income, operating income, and transfer payments, but not as-set income. The other type of study is based on household microdata. Wang et al. [15] indicated that digital finance increased non-agricultural revenue, but decreased agricultural income. On the basis of subdividing the income structure, Zhang et al. [16] revealed that digital finance increased wage income and reduced operating income and agricultural income, but had no effect on property income and transfer income. Wang et al. [17] found that using digital finance increased self-operated industrial and commercial income and reduced planting income, but did not affect forestry income, animal husbandry income, or labor income. Thirdly, the analysis of the path by which digital finance affects farmers' income has been considered. From the county perspective, Zhang [18] attested that digital finance could indirectly promote farmers' income growth through county industrial upgrading. Wang et al. [15] found from a micro perspective that digital finance could promote entrepreneurship and non-agricultural employment in rural households, thereby increasing family income.

To sum up, the existing literature provides a relevant theoretical and empirical basis for this study. However, there are still areas for improvement: First, in terms of research objects, existing studies have analyzed farmers as a whole, ignoring the particularity of professional farmers. Professional farmers are the backbone of rural revitalization in typical agricultural areas, unlike part-time farmers and non-farmers. Agricultural income is their primary source of income. Therefore, the impact of digital finance on the income of different types of farmers may differ. Second, regarding research content, the existing research conclusions regarding digital finance's impact on rural households' income structure are still controversial. In addition, regarding the impact mechanism, the existing research focuses more on the role of non-agricultural employment. We require analyses of how digital finance affects farmers' income paths from different sources. So, what impact does digital finance have on the income of professional farmers? What is its path of action? This is an important issue worthy of in-depth study and discussion.

Given this, this paper takes the professional apple growers in the typical areas of Shaanxi as the research object (according to previous research conclusions, the income of apple planting households in China accounts for more than 76% of the total household income, and is typical of professional farmers [19]). It explores the impact of professional farmers' digital financial involvement behavior on their income by using the OLS model, 2SLS model, and other methods. Furthermore, we used the intermediary effect model to deeply excavate the mechanism by which digital finance affects the internal income structure of professional farmers, and tried to clarify the overall picture of digital finance concerning the income of professional farmers.

The marginal contribution of this paper is mainly reflected as follows: first, it pays attention to the particularity of professional farmers in typical agricultural areas and profoundly analyzes the specific paths of digital financial involvement affecting the income of professional farmers from different sources, which enriches the relevant research in the field of digital finance; second, the research conclusion of this paper can provide a valuable reference for formulating differentiated policies on digital financial services for rural revitalization.

2. Theoretical Analysis and Research Hypothesis

As a product of the deep integration of digital technology and financial services, digital finance, in theory, mainly affects the total income of professional farmers through two mechanisms: direct and indirect. One is directly affects the total household income by increasing property income and transfer payment; the other promotes productive agricultural investment and farmers' family entrepreneurship, which affects agricultural income, wage income, and self-employed industrial and commercial income, and indirectly affects the total household income.

2.1. The Direct Mechanism of Digital Finance Affecting Professional Farmers' Income

The immediate impact of digital finance on the income of professional farmers is mainly achieved by increasing property income and transfer income. Due to the scattered living arrangement of rural households, traditional financial institutions rarely set up physical bank branches in rural areas due to cost and benefit considerations. Suppose farmers need to purchase financial wealth management products. In that case, they usually need to go to the bank branches in townships or counties, which significantly increases the time cost and transportation cost to farmers. In addition, traditional banks can provide minimal wealth management channels, and farmers can only invest through individual channels such as current savings. It is challenging to obtain capital gains with higher interest rates [20]. The emergence of digital finance has effectively broken through the traditional transaction model's dependence on physical financial outlets and the constraints of business hours. Farmers can purchase wealth management products that meet their needs on internet financial platforms anytime, anywhere, significantly reducing transaction costs and improving financial efficiency and investment efficiency [21]. For example, Alipay provides farmers with a convenient and low-threshold investment platform. Farmers can use their idle funds to purchase wealth management products and obtain related interest, which effectively broadens the household income source [8]. In addition, digital finance can also rely on information and technological advantages to make accurate portraits of farmers, identify their potential financial needs, and then meet their needs through innovative financial products, effectively improving the matching between financial supply and demand [22]. The diversification of rural households' financial assets will help increase property income, which will directly affect the total household income.

Secondly, in terms of increasing transfer income, the transfer income of farmers mainly includes government transfer payments and gifts between families. Regarding government transfers, there are three main deficiencies in rural fiscal transfer payments in China. (1) The transparency of fiscal transfer payments is low, and there is no scientific basis for distribution, so it is greatly affected by human factors, making it challenging to ensure the fairness and reasonableness of transfer payments. (2) The use of funds is not clear. The purpose of the transfer payments is to achieve the equalization of public services, regulate regional differences, and coordinate urban and rural development. However, the current targets of fiscal transfer funds are often not clear enough to play a practical role. (3) Supervision and management are not in place. Special appropriations need necessary supervision and management to ensure that funds are used for their designated purposes, and improve the efficiency of fund use. However, the use of financial support funds for agriculture is not satisfactory. Not only is its input scattered, and the management departments are diversified, but there is also a serious problem of duplicate investment, which greatly affects the efficiency of the use of special funds related to agriculture. The development of digital finance, in addition to promoting the growth of local tax revenue by expanding the tax base and improving the efficiency of tax collection and management [23], and then improving the government's efforts in rural transfer payments [24], has also significantly improved the transparency, accuracy, and management efficiency of transfer payments [25]. For example, in response to the drought, the government of Niger implemented a cash transfer payment plan based on mobile phone delivery, and distributed disaster relief funds to affected farmers through the mobile transfer system. This has reduced payment costs, while improving payment efficiency and significantly increasing farmers' income [26]. The second is in the area of inter-family transfers. Before the advent of mobile payment services, farmers who wanted to send money to their families often needed to send money to the post office or bank, or ask an acquaintance to help bring it back. The emergence of mobile payment has greatly facilitated farmers in obtaining remittances and other transfer payments from relatives and friends [27]. For example, Munyegera et al. [28] found that rural households using mobile payments are more likely to receive remittances. The amount of remittances received here is significantly higher than that of families without mobile payments. In addition, red envelopes for festivals, weddings, funerals, and birthdays can also be collected through mobile payments, which increases the total household income to a certain extent [29].

2.2. The Indirect Mechanism of Digital Finance Affecting Professional Farmers' Income

Digital finance mainly affects agricultural, wage, and self-employed industrial and commercial income by promoting productive agricultural investment and farmers' family entrepreneurship. It indirectly influences the total household income. First, it affects agricultural income and wage income. Professional farmers need a lot of money to purchase productive materials such as fertilizers and pesticides in the production process. It is challenging to maintain only their limited capital accumulation. Therefore, credit funds have become an important source of financial support for farmers [30]. However, the phenomenon of financial exclusion in rural areas still exists widely at present, and the problem of financing constraints restricts the production enthusiasm of farmers, which is not conducive to the normal development of agricultural production [31]. Digital finance can affect farmers' credit availability in two ways. One is to reduce information asymmetry. As digital technology develops, financial institutions can use big data, artificial intelligence, and other technologies, combined with Taobao, WeChat, and other scenarios, to deeply mine and analyze user social media and online shopping platform data, and obtain a large amount of helpful information for evaluating loan risks. Information that helps to achieve a more accurate portrait of the borrower effectively alleviates the degree of information asymmetry [32,33]. The second is to reduce transaction costs. With the help of digital technology, farmers can directly realize the entire operation of loans online, on mobile terminals, changing how farmers access finance, making it no longer limited by time and location, and significantly reducing transaction costs [34]. With the relaxation of financing constraints and increased agricultural production funds, farmers can invest more in fertilizers, pesticides and technology, and hire labor to increase agricultural output [11]. For example, Abdul Rahman et al. [35] collected micro-survey data of smallholder farmers in northern Ghana, and assessed the impact of mobile money on farmers' production inputs and outputs. The results show that those who adopted the technology applied 18% and 13% more fertilizers and herbs than those who did not. The output of adopters increased by about 4%. At the same time, digital finance has also given birth to new business models that combine online and offline approaches, such as rural Taobao and direct sales of origin, which effectively broadens the sales channels of agricultural products and thereby increase agrarian income [12,36]. For a professional farmer, the increase in agricultural production investment will enable them to focus more on agricultural production, reducing the time available for a family to go out to work, thereby reducing family wage income [37].

Second, as regards the effect on self-operated industrial and commercial income, for potential entrepreneurial farmers with a low level of self-owned wealth and a lack of mortgage assets, since entrepreneurial activities often have a minimum capital threshold, financing constraints make it challenging to cross the threshold of entrepreneurial capital, thus restricting the entrepreneurial activities of farmers [38]. With the help of digital technologies such as big data and cloud computing, financial institutions can use non-financial data such as personal consumption behavior and transaction information to provide credit ratings for farmers who lack credit records, and provide corresponding credit support, thereby providing possibilities for farmers to start businesses [6]. In addition to having financial attributes, digital financial platforms also have specific social functions. Taking WeChat as an example, this platform primarily provides instant messaging services, promotes communication and exchanges between people, and enhances social interaction and trust. In addition, it also provides services such as payment functions and red envelope transfers. These social functions supported by digital finance are conducive to shortening the distance between relatives and friends and maintaining good interpersonal relationships [39]. Furthermore, the social relationship network promoted by digital finance makes entrepreneurs more likely to communicate with people or other entrepreneurs with different knowledge backgrounds, experience backgrounds, and cultural backgrounds, enabling them to obtain diversified entrepreneurial knowledge and financial information, which will help improve the financial literacy and entrepreneurial awareness of farmers, thereby enhancing their entrepreneurial motivation [40]. Therefore, the alleviation of credit constraints and the strengthening of social networks can effectively promote farmers' entrepreneurship, thereby increasing household self-operated industrial and commercial income [41].

Based on the above analysis, we develop the following research hypotheses:

H1. *Digital financial involvement affects the total income of professional farmers mainly through direct and indirect mechanisms;*

H1a. *Digital financial involvement can directly increase the property income and transfer income of professional farmers;*

H1b. *Involvement in digital finance indirectly reduces wage income by reducing the time available for going out to work (in China, due to the division of urban and rural areas caused by the household registration system, it is common for farmers to work side-by-side). Migrant workers work in non-agricultural employment, such as in cities;*

H1c. *Digital financial involvement indirectly increases agricultural income by promoting productive agricultural investment;*

H1d. *Involvement in digital finance indirectly increases self-employed industrial and commercial income by promoting household entrepreneurship.*

3. Research Design

3.1. Data Sources and Samples' Basic Features of Farmer Households' Digital Finance Involvement

The data used come from the field research completed by the research team in the typical apple-producing areas of Shaanxi Province from November to December 2020. To ensure good representativeness of the survey data, according to the principle of multi-stage stratified sampling and the sampling method of probability and scale ratio, the research team selected Baota District and Luochuan County of Yan'an City, and Fengxiang District of Baoji City, as sample areas. We randomly selected three towns in each sample area, set three to four sample villages in each town, and selected 30–40 sample households randomly in each sample village for a face-to-face questionnaire survey. The specific mode of selecting farmers is that after getting the roster of farmers from the village committee of the sample village, the farmers were divided into three groups according to the scale of apple planting. Then, 10 to 14 farmers were randomly placed in each group. The total sample number of households was controlled between 30 and 40, and face-to-face interviews were conducted. This survey obtained 1030 valid samples.

It should be noted that the apple-planting area and output of Shaanxi Province rank first in the country, so we have here chosen the professional farmers in the main apple-producing areas of Shaanxi Province as the survey object, which is typical. In addition, this survey intends to select professional farmers from professional apple-planting villages. In the sample villages, the average proportion of households specializing in apple cultivation accounted for 80.19% of the total households. This shows that the research samples selected in this paper are representative, and the conclusions are reliable.

According to the sample farmers' understanding of digital financial services, 724 farmers chose "not at all", accounting for 70.29% of the sample; 261 households chose "have heard of it", accounting for 25.34% of the sample; 29 rural households chose "general", accounting for 2.82% of the sample; 13 households chose "relatively familiar", accounting for 1.26% of the sample; only 3 households chose "very familiar", accounting for only 0.29% of the sample. Regarding digital payment, 652 households have used digital payment (Alipay, WeChat Pay, etc.), accounting for 63.30% of the sample; 378 households have not used digital payment, accounting for 36.70% of the sample. Looking further, 647 rural households used digital payment for daily consumption, accounting for 62.82% of the sample; 481 rural households used digital payment to pay for productive expenditure, accounting for 46.70%. In addition, the sample farmers used digital payment 17.36 times a week on average. In terms of digital wealth management, 81 rural households have purchased wealth management products from digital financial platforms, accounting for 7.86% of the total sample. In terms of digital credit, 75 rural households have obtained loans from digital financial platforms, accounting for 7.28% of the total sample households; the minimum annual interest rate of loans was 3%, the highest was 10%, and the minimum loan period was one month, while the longest was three years. On Alipay and other digital financial platforms, the loan interest rate and loan period are generally determined using big data technology based on farmers' credit, income, and consumption levels.

The above statistical results show that, as a new concept, digital finance still needs to be improved in terms of the understanding and acceptance of sample farmers. Among them, digital payment is the most widely used, and participation in digital wealth management and digital credit needs to be improved. This implies that the future development of digital finance in rural areas needs to focus on breakthroughs in digital wealth management and digital credit. In addition, digital finance is a transfer payment tool. Farmers can bind personal and relative social security accounts on Alipay and WeChat. Furthermore, the government can directly transfer subsidies to farmers' accounts through the digital financial platform.

3.2. Variable Design

3.2.1. The Explained Variable

The total income of rural households refers to the sum of agricultural income, wage income, self-employed industrial and commercial income, property income, and transfer income.

3.2.2. Core Explanatory Variables

Drawing on the research results of He et al. [42], this paper examines the involvement of farmers in digital finance via the three dimensions of digital wealth management, digital credit, and mobile payment. Specifically, this article asks farmers, "Have you ever used digital wealth management products such as Yu'e Bao and wealth management APPs?". Furthermore, "Have you ever used mobile payment services such as WeChat Pay and Alipay?" If a farmer has participated in any digital wealth management, digital lending, and digital payment, it is here considered that the farmer has experience in digital finance.

Among the samples, 653 households participated in digital finance, accounting for 63.40% of the valid samples, and 377 households did not participate in digital finance, accounting for 36.60% of the valid samples.

3.2.3. Control Variables

Based on the relevant literature and available data, personal characteristics, family characteristics, and regional feature variables are selected as the control variables to reduce the estimation bias. This article has chosen the head of household's age, education, health status, and whether they are a village cadre to characterize the individual characteristics of the head of the household. In general, as the head of the household ages, their productive capacity will gradually decline, which will suppress income growth. The higher the education level of the head of the household, the stronger their management ability, which is more conducive to promoting income growth. The better the health of the head of household, the more conducive it is to achieving higher gains in agricultural production, thereby contributing to income growth. If the head of the household is a village cadre, they can obtain more information about apple production through their network, optimize their production decisions, and thus increase income [17].

This article selects the family size, family labor force, social capital, family farmland endowment, apple planting years, the total value of agricultural machinery, agricultural technology training, and cooperative membership to characterize the families. Large family sizes mean that the family has abundant labor resources, and can thus produce more income. China's rural society is a typical humanistic society; the more rural households share favors, indicating that their social networks are more developed, and they can derive more valuable information from the relationship network, which can promote family income growth. The larger the scale of farmland, the more conducive it is to achieving large-scale operations and increasing household income [15]. The higher the number of apple-planting years, the more experienced the farmer will be in planting apples, and the more conducive it is to increasing the level of apple production, thereby increasing household income. A high level of agricultural mechanization means that farmers have higher productive forces and are more likely to earn higher income through agricultural production. Participation in agricultural technology training can help improve the production and management capabilities of professional farmers, which in turn can improve the quality and yield of agricultural products to achieve agricultural income growth. Farmers often face higher information thresholds and asymmetries when connecting to markets. Cooperatives can effectively link farmers with product markets and factor markets, which can improve transaction efficiency and thus increase income.

Considering that household income is also affected by regional characteristics, this paper has introduced regional dummy variables (the samples are located in Luochuan and Pagoda) to control the regional fixed effects.

The assignment description and descriptive statistics of the above variables are shown in Table 1.

Table 1. Variable meaning and descriptive statistics.

Variable	Description	Mean	S.D.
Income	Total household income level in 2020, unit: CNY; logarithm	11.11	0.94
Digital finance involvement	yes = 1, no = 0	0.63	0.48
Age	The actual age of the head of household, unit: years old	54.94	9.37
Education	The actual number of years of education received by the head of household, unit: year	7.29	3.44
Health status	Household head's self-evaluation of health status: very unhealthy = 1; relatively unhealthy = 2; general = 3; relatively healthy = 4; very healthy = 5	3.93	1.09

Table 1. *Cont.*

Variable	Description	Mean	S.D.
Village cadres	Whether the head of household is a village cadre: yes = 1; no = 0	0.11	0.31
Family size	Total family population, unit: PCS	4.23	1.61
Household labor force	The total number of the household labor force, unit: PCS	2.64	1.02
Social capital	The total expenditure of family favors in 12 months, unit: CNY, take the logarithm	8.10	1.11
Family farmland endowment	The area of farmland managed by the household, unit: mu	12.99	18.59
Apple-planting years	How many years has the family grown apples, unit: year	21.75	9.13
Total value of agricultural machinery	The total value of household agricultural machinery, unit: CNY, logarithm	9.18	1.91
Agricultural technology training	Whether the family uses agricultural technology training: yes = 1; no = 0	0.55	0.50
Cooperative membership	Whether they have joined the cooperative: yes = 1; no = 0	0.15	0.36
0.32 0.46 0.32 0.32 0.47 0.32 11.11 0.94 11.11 0.63 0.48 0.63 The sample is located in Luochuan	Luochuan = 1, others = 0	54.94	9.37
The sample is located in the pagoda	Pagoda = 1, others = 0	7.29	3.44

Note: Fengxiang is the control group in the sample area.

3.3. Empirical Methods

3.3.1. Benchmark Regression—OLS Model

To estimate the impact of digital financial involvement on the income of professional farmers, we constructed the following model:

$$Income_i = \alpha + \beta D_i + \gamma Z_i + \varepsilon_i \tag{1}$$

In Equation (1), $Income_i$ represents the income level of the ith professional farmer, D_i represents the digital financial involvement of the ith professional farmer, Z_i is a control variable, α, β and γ are the parameters to be estimated, and ε_i is the random disturbance item. The variables in the model have been converted to logarithms.

3.3.2. Discussion of Endogeneity—2SLS Model

The decision of whether or not to participate in digital finance was likely to give rise to endogenous problems due to omitted variables, reverse causality, etc. To solve this problem, referring to the research ideas of Dong et al. [38] and He et al. [42], this paper selects the average level of digital financial involvement of other rural households after grouping by county and age of respondents as the instrumental variable of digital financial involvement. According to the behavioral imitation theory, whether farmers used digital financial services in rural acquaintance communities is affected mainly by the average level of digital financial involvement in the same age group. Hence, a greater possibility of digital finance use satisfies the correlation of instrumental variables. The average level of digital financial involvement in the same age group generally did not directly affect the income level of farmers, thus satisfying the exogenous nature of instrumental variables. The specific steps for selecting instrumental variables were as follows: dividing the sample farmers into five sub-samples according to age (20–30 years old, 30–40 years old, 40–50 years old, 50–60 years old, and over 60 years old), and then selecting the average level of digital financial involvement of the sample farmers in the same age group and county as an instrumental variable. In this paper, the two-stage least squares (2SLS model) method is used to estimate the regression, and the specific model settings are as follows.

The first stage estimation equation:

$$D_i = \delta + \varphi IV_i + \gamma Z_i + \mu_i \tag{2}$$

The second stage estimation equation:

$$Income_i = \alpha + \beta \hat{D}_i + \lambda Z_i + \varepsilon_i \tag{3}$$

In Equations (2) and (3), IV_i is the instrumental variable, $\hat{D}_i$ is the predicted value of D_i, δ is the parameter to be estimated, and μ_i is the random disturbance item. The other variables have the same meaning as those in Equation (1).

3.3.3. Correcting Selective Bias—Propensity Score Matching (PSM) Method (1)

The specific steps of the propensity score matching method were as follows.

In the first step, covariates were selected. In this paper, the personal characteristics of the head of the household (age, education level, health status, whether they are a village cadre), family characteristics (family size, family labor force, social capital, family farmland endowment, apple-planting years, the total value of agricultural machinery, whether they use participate in agrarian technology training, whether they have joined a cooperative), and regional dummy variables (the samples are located in Luochuan and Pagoda) were selected as covariates.

In the second step, the propensity score (PS value) was calculated. In this paper, the Logit model was used to calculate the propensity score of individual i participating in digital finance.

In the third step, propensity score matching was performed. (1) Select the matching method. In this paper, four typical methods were used for matching. ① K-nearest neighbor matching, i.e., matching by finding the k different groups of individuals with the nearest propensity score. In this paper, k was set to 4 for one-to-four matching to minimize the mean squared error. ② Caliper matching, i.e., limiting the absolute distance between propensity scores. In this paper, the caliper range was set to 0.02. ③ K-nearest neighbor matching within the given caliper range. In this paper, the caliper range was set to 0.02 for one-to-four matching. ④ Kernel matching. In this paper, we used the default kernel function and bandwidth. If the results of different matching methods were similar, the matching results were robust and did not depend on the specific method. (2) Test for equilibrium. If the propensity score were to be estimated more accurately, the standardized deviation could be used to test the treatment group after the X_i was matched.

In the fourth step, the average treatment effect was calculated. The expression is as follows:

$$ATT = E\left[Y_1^i - Y_0^i\right] = E\left[Y_1^i - Y_0^i | D = 1\right] = E\left[Y_1^i | D = 1\right] - E\left[Y_0^i | D = 0\right].\ i \in (I + J) \quad (4)$$

In Equation (4), Y_1^i and Y_0^i represent the total household income of rural households participating in digital finance and those not participating in digital finance, respectively. D = 1 indicates the farmer is participating in digital finance (treatment group I). D = 0 indicates that the farmer is not participating in digital finance (control group J).

3.3.4. Correcting Selective Bias—Inverse Probability Weighting Regression Adjustment (IPWRA) method (2)

The PSM method is prone to estimation bias if there are problems such as miss-setting or improper selection in observable variables in the first stage. Therefore, this paper further used the reverse probability weighting regression adjustment (IPWRA) method for empirical analysis. The IPWRA method is doubly robust; that is, if either the selection equation or the outcome equation is set correctly, we can consistently estimate the income effect of digital finance. The ATT measured by the IPWRA method is more robust than the PSM method. The IPWRA model was estimated in three steps: the first step was to use the Logit model to estimate the propensity score and calculate the inverse probability weight. The second step was to use the inverse probability weight calculated in the first step to estimate the income equation and then calculate the predicted income of the individual. The third step was to calculate the mean income under different treatments (digital financial participation or non-participation), and the difference between the two groups of income mean was the impact of digital financial participation on farmers' income. The ATT of the IPWRA method can be expressed as follows:

$$\tau_{ATT}^{IPWRA} = \frac{1}{N}\sum_{i=1}^{N} Y_i \left\{ \left[\frac{P(X_i)}{1+P(X_i)} \mid D_i = 1 \right] - \left[\frac{P(X_i)}{1+P(X_i)} \mid D_i = 0 \right] \right\} \tag{5}$$

In Equation (5), $P(X_i)$ is the propensity score. X_i is the control variable, which is consistent with the control variables of the benchmark regression model. D_i = {0, 1} is a dummy variable, D_i = 1 indicates the farmer is participating in digital finance, and D_i = 0 indicates that the farmer is not participating in digital finance.

4. Results of Empirical Analysis

4.1. Benchmark Regression Results

From Table 2, only controlling the core explanatory variables, the robustness of the model was tested by gradually introducing the variables of the household head's personal characteristics, family characteristics, village characteristics, and regional characteristics. Overall, our model worked well. Furthermore, the regression results in column (5) show that involvement in digital finance significantly positively impacts the total income of professional farmers, indicating that involvement in digital finance can help increase the total income of professional farmers. This partially verifies Hypothesis 1.

Table 2. Benchmark regression results of the effects of digital financial involvement on the total income of professional farmers.

Variable	(1)	(2)	(3)	(4)
Digital finance involvement	0.340 *** (0.058)	0.298 *** (0.065)	0.232 *** (0.060)	0.243 *** (0.059)
Age		0.001 (0.004)	−0.002 (0.003)	−0.005 (0.003)
Education		0.018 ** (0.009)	0.007 (0.008)	0.012 (0.009)
Health status		0.058 ** (0.030)	0.036 (0.028)	0.033 (0.027)
Village cadres		0.029 (0.087)	−0.007 (0.085)	0.019 (0.085)
Family size			0.066 *** (0.020)	0.075 *** (0.020)
Household labor force			0.177 *** (0.032)	0.150 *** (0.032)
Social capital			0.034 (0.024)	0.042 * (0.025)
Family farmland endowment			0.006 *** (0.001)	0.006 *** (0.002)
Apple-planting years			0.007 ** (0.003)	0.013 *** (0.003)
Total value of agricultural machinery			0.062 *** (0.016)	0.079 *** (0.016)
Agricultural technology training			0.100 * (0.057)	0.097 * (0.056)
Cooperative			0.146 ** (0.071)	0.134 * (0.071)
The sample is located in Luochuan				−0.441 *** (0.070)
The sample is located in Baota				−0.152 ** (0.065)
Constant value	10.891 *** (0.045)	10.485 *** (0.261)	8.992 *** (0.324)	9.021 *** (0.334)
R^2	0.032	0.042	0.174	0.205
Observations	1030	1030	1030	1030

Note: ***, ** and * indicate that the estimated coefficients are significant at 1%, 5%, and 10%, respectively; the values in brackets are robust standard errors. Data source: Calculated by the software STATA 14.0.

Both the family size and the number of family laborers have a significant positive impact on the total income of professional farmers. The possible reason for this is that with a larger family size, more abundant labor resources are available. Correspondingly, the more income it can create, the more beneficial it is to increase family income [43]. Social capital is significantly positively correlated with the total income of professional farmers.

The possible reason for this is that, according to the "human relationship hypothesis", the richer the social capital, the more valuable the information that can be obtained from the relational network, and the more helpful it is to increase family income [44]. The impact of family farmland endowment on the total income of professional farmers is significantly positive, and the possible reason for this is that, in terms of family farmland, the higher the endowment, the more conducive it is to realizing scale operation and increasing family income. There is a significant positive correlation between the years of apple planting and the total income of professional farmers. The possible reason for this is that the longer the planting period and the higher the level of planting technology, the more conducive it is to increasing the apple production level, thereby increasing family income. The impact of the total value of agricultural machinery on the total income of professional farmers is significantly positive. The possible reason for this is that the higher the total value of agricultural machinery, the higher the level of agricultural mechanization, and the more favorable this is to increasing family income [45]. Agricultural technology training is significantly positively correlated with the total income of professional farmers' families. The possible reason is that farmers' involvement in agricultural technology training can help improve their production and management capabilities, thereby increasing family income [46]. The impact of cooperatives on the total income of professional farmers is significantly positive. The possible reason for this is that farmers joining cooperatives can effectively improve the market bargaining power of agricultural products, which is conducive to improving the family income level [47]. When the sample is located in Luochuan or Baota, the total household income has a significant negative impact. The possible reason is that compared with Luochuan County and Baota District, Fengxiang District is the closest to Xi'an, the provincial capital, with many non-farm employment opportunities and a wide range of income sources, which is more conducive to promoting farmers' income.

4.2. Endogeneity Discussion

Table 3 shows the 2SLS regression results of digital financial involvement on the total income of professional farmers. In Table 3, the regression results of the first stage show that the average level of digital financial involvement in the same age group in the same county had a significantly positive effect on the digital financial involvement of professional farmers, indicating that the instrumental variables met the correlation requirements. From the endogenous test results, it can be seen that the Hausman test results reject the null hypothesis at a significance level of 10%; that is, there is an endogenous problem. Considering that the Hausman test is no longer valid under heteroscedasticity, the DWH test was also used in this paper, and the results show that the Durbin–Wu–Hausman test rejects the null hypothesis at a significance level of 5%, which enables us to conclude that digital finance involvement is an endogenous variable. In addition, the Cragg–Donald Wald F statistic is 22.876, which is higher than the critical value of 16.38 at the 10% level; there is no weak instrumental variable problem. The regression results of the second stage show that after correcting the possible endogenous bias of the model, digital financial involvement still has a significant positive effect on the total income of professional farmers, suggesting that digital financial involvement will significantly increase the total income of professional farmers. This partially validates Hypothesis 1 once again.

Table 3. 2SLS regression results of digital financial involvement on the total income of professional farmers.

Variable	The First Stage	The Second Stage
Digital finance involvement		1.009 ** (0.418)
The average level of digital financial involvement in the same age group in the same county	0.519 *** (0.118)	

Table 3. *Cont.*

Variable	The First Stage	The Second Stage
Cragg–Donald Wald F-statistic	22.876	
Hausman test	3.33 *	
Durbin–Wu–Hausman test	4.040 **	
Control variable	Controlled	Controlled
Observations	1030	

Note: ***, ** and * indicate that the estimated coefficients are significant at 1%, 5%, and 10%, respectively; the values in brackets are robust standard errors. Data source: Calculated by the software STATA 14.0.

4.3. Correcting Selective Bias

The 2SLS model was used to overcome the endogenous problem as much as possible, but due to the limitations of data and variables, the impact of digital financial participation on the total household income of professional farmers may still be interfered via "self-selection", resulting in a selection bias in the regression results. Therefore, this paper used the propensity score matching method to construct a counterfactual analysis framework for digital financial participation in the total household income of professional farmers, so as to overcome the potential selection bias problem of the model, and the estimated results are shown in Table 4.

Table 4. Estimation results of PSM method and IPWRA method.

Method	Matching Type	Treatment Group	Control Group	ATT	S. D.	T-Value
PSM	K-nearest neighbor matching (k = 4)	11.225	10.987	0.238 ***	0.085	2.81
	Caliper matching (caliper = 0.02)	11.223	10.979	0.244 ***	0.082	2.99
	K-nearest neighbor matching within the caliper (k = 4, caliper = 0.02)	11.223	10.986	0.238 ***	0.084	2.82
	Kernel matching	11.223	10.983	0.240 ***	0.081	2.97
IPWRA	-	-	-	0.226 ***	0.071	3.18

Note: *** indicates that the estimated coefficients are significant at 1%. Data source: Calculated using the software STATA 14.0.

It can be seen from Table 4 that given the measured covariates, the ATT values obtained by the four matching methods (K-nearest neighbor matching, caliper matching, K-neighbor caliper matching, and kernel matching) are 0.238, 0.244, 0.238, and 0.240, respectively. Although the coefficient values obtained by the four methods are slightly different, they are all significantly positive at the 1% statistical level. The average value of ATT is 0.240 ((0.238 + 0.244 + 0.238 + 0.240)/4 = 0.240). That is, compared with the total household income of professional farmers who do not participate in digital finance, the total household income of professional farmers participating in digital finance is 27.12% higher (exp (0.240)-1). After eliminating the observed systematic differences between samples, the use of digital finance still had a significant positive impact on farmers' income, which is consistent with the previous empirical results and further verifies the robustness of the results.

However, PSM only sets an intervention model, and it will inevitably produce biased estimation results when the intervention model is set incorrectly. For this reason, this paper refers to the research of Ma et al. [48] and adopts the more robust inverse probability weighting regression adjustment (IPWRA) method to correct it. The estimation results show that the value of ATT estimated by the IPWRA method is 0.226, which is significant at the 1% statistical level. Furthermore, by comparing the estimated values of IPWRA and PSM, it is found that the estimated value of IPWRA is lower than the estimated value of PSM, which proves that PSM will overestimate the impact effect. Although the estimated values of IPWRA and PSM are different, they all have significant positive effects, which indicates that the conclusions of this study are robust.

4.4. Robustness Test

To eliminate the family size's impact on professional farmers' income, this paper replaces the explanatory variable with the per capita total income of professional farmers. The regression results are shown in Table 5. From the estimated results in the second section on Table 5, it can be seen that after correcting possible endogenous biases, the impact of digital finance involvement on the per capita total income of professional farmers is significantly positive, showing that involvement in digital finance can effectively broaden farmers' income-increasing channels, thereby improving gross family income per capita. Thus, Hypothesis 1 was partially confirmed.

Table 5. 2SLS regression results of digital financial involvement on professional farmers' per capita total income.

Variable	The First Stage	The Second Stage
Digital finance involvement		0.931 ** (0.411)
The average level of digital financial involvement in the same age group in the same county	0.519 *** (0.118)	
Cragg–Donald Wald F-statistic	22.876	
Durbin–Wu–Hausman test	3.345 *	
Control variable	Controlled	Controlled
Observations	1030	

Note: ***, ** and * indicate that the estimated coefficients are significant at 1%, 5%, and 10%, respectively; the values in brackets are robust standard errors. Data source: Calculated by the software STATA 14.0.

5. Further Analysis: Mechanism of Action and Heterogeneity

5.1. Analysis of the Impact Mechanism

According to the above research results, it can be seen that the income-increasing effect of digital finance is significant. So, what is the mechanism by which digital finance affects the income of professional farmers? To this end, this part discusses how digital finance specifically affects the internal income structure of farmers. In addition, considering that there are a large number of zero values in the data of wage income, self-employment industrial and commercial income, property income, and transfer income, the Tobit model needs to be employed for empirical testing, but since the variable digital financial involvement is a binary dummy variable rather than a continuous variable, the IV-Tobit model is not applicable at this time (the IV-Tobit model is only applicable when the core explanatory variable is a continuous variable). Therefore, this article employs the Conditional Mixed Process (CMP) proposed by Roodman [49] for empirical testing. It should be noted that, as agricultural income is a continuous variable, the Conditional Mixed Process (CMP) is still applicable. The regression results show that the regression results of the CMP method are consistent with the 2SLS model. Still, for the convenience of analysis, this paper only reports the estimation results based on the CMP method. The specific regression results are shown in Tables 6 and 7.

Table 6. The impact of digital finance on the income of professional farmers: direct impact mechanisms.

Variable	Property Income		Transfer Income	
	The First Stage	The Second Stage	The First Stage	The Second Stage
Digital finance involvement		11.335 (17.797)		0.155 (1.401)
The average level of digital financial involvement n in the same age group in the same county	0.519 *** (0.117)		0.519 *** (0.117)	
Atanhrho_12	−0.299 (0.471)		0.026 (0.209)	
Control variable	Controlled	Controlled	Controlled	Controlled
Observations	1030	1030	1030	1030

Note: *** indicates that the estimated coefficients are significant at 1%; the values in brackets are robust standard errors. Data source: Calculated by the software STATA 14.0.

Table 7. Impact of digital finance on professional farmers' income: indirect impact mechanisms.

Variable	**Wage Income**	**Agricultural Income**	**Productive Investment in Agriculture**	**Agricultural Income**	**Self-Employed Business Income**	**Home Business**	**Self-Employed Business Income**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Digital finance involvement	−0.550 (3.126)	2.880 *** (0.386)	1.417 *** (0.197)	2.524 *** (0.434)	45.255 * (24.198)	0.206 ** (0.102)	0.089 (0.138)
Productive investment in agriculture				0.866 *** (0.183)			
Home business							9.446 *** (0.224)
The first stage estimation—whether to participate in digital finance							
The average level of digital financial involvement in the same age group in the same county	0.519 *** (0.117)	1.002 *** (0.374)	0.752 *** (0.278)	1.061 *** (0.387)	0.519 *** (0.117)	0.519 *** (0.117)	0.519 *** (0.117)
Atanhrho_12	0.060 (0.204)	−0.815 *** (0.180)	−1.417 *** (0.239)	−0.760 *** (0.198)	−0.765 * (0.416)	−0.346 * (0.190)	−0.142 (0.168)
Control variable	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
Observations	1030	1030	1030	1030	1030	1030	1030

Note: ***, ** and * indicate that the estimated coefficients are significant at 1%, 5%, and 10%, respectively; the values in brackets are robust standard errors. Data source: Calculated by the software STATA 14.0.

It can be seen from Table 6 that digital financial involvement has no significant impact on property income and transfer income, but the estimated coefficient is positive. The possible reason is that although digital finance has developed rapidly in rural areas, due to the generally low level of financial literacy in rural households, it is restricted to the use of digital financial platforms to activate financial assets through financial management and other means, so digital finance has a negative impact on asset income. The promotion effect has not yet been shown [14]. The transfer income in this paper mainly consists of three items: agricultural subsidy income, social security income, and gift income from relatives and friends. First of all, regarding agrarian subsidy income and social security income, the current government departments mainly transfer various agricultural subsidy funds or social security funds directly to farmers' accounts through one card (discount) payment method. This also reflects that the functional role of digital finance in improving the efficiency of fiscal capital allocation has not yet emerged. Secondly, as far as the income from relatives and friends is concerned, it can be incorporated through mobile payments or mobile bank transfers; however, due to the constraints of the "digital divide", 36.60% of the sample farmers have not used digital financial services. This also implies that in the future, digital finance will have an enormous potential ability to increase property income and transfer income, and will be a new growth point for farmers to increase their income. At this point, H1a is not verified.

Furthermore, Table 7 reports the indirect mechanism by which digital finance affects the income of professional farmers. Digital finance involvement has a negative impact on wage income, which is consistent with theoretical expectations, although the result is not statistically significant. The possible reason is that digital finance can alleviate the financing constraints of professional farmers and help them increase production input and expand their scale. Apple is a labor-intensive cash crop that requires a lot of labor input in the production process, so it will reduce family members going out to work, thereby reducing family wage income [36]. Hypothesis H1b is not verified.

From the second column of Table 7, it can be seen that the involvement of digital finance has a significant positive impact on agricultural income. The results in column 3 of Table 7 show that the involvement of digital finance has a significant positive impact on productive agricultural investment, indicating that professional farmers' involvement in digital finance can effectively alleviate their financing constraints and promote their productive agricultural investment. The results in column (4) of Table 7 show that digital financial involvement and effective agricultural investment significantly positively impact on agricultural income after adding the agricultural productive investment variable in the benchmark model. It can be seen that the intermediary effect of productive agricultural investment on agricultural income is significant; that is, professional farmers' digital financial involvement can increase their agricultural income by promoting effective agricultural investment. At this point, Hypothesis H1c is verified.

It can be seen from column (5) of Table 7 that digital finance has a significant positive impact on self-employed industrial and commercial income. From column (6) of Table 7, it can be seen that the involvement of digital finance has a significant positive impact on the entrepreneurship of professional farmers, indicating that involvement in digital finance can effectively alleviate the financing constraints and information constraints of potential entrepreneurial professional farmers, thereby increasing their entrepreneurial probability. The results in column (7) of Table 7 show that after adding the entrepreneurship variable to the benchmark model, the impact of digital financial involvement on self-employed industrial and commercial income is no longer significant. However, the effect on entrepreneurship is still substantial, and the regression coefficient is positive. Therefore, according to the mediation effect judgment standard, in the path of digital financial involvement affecting the income of self-operated industrial and commercial households, professional farmers' family entrepreneurship has a complete intermediary effect; that is, digital finance mainly increases the income of self-operated industrial and commercial households by promoting professional farmers' family entrepreneurship. Thus, Hypothesis H1d is verified.

5.2. Heterogeneity Analysis

The article verifies the promoting effect of digital financial involvement on the total income of professional farmers. Next, we will conduct a heterogeneity analysis according to the education level, the farmland management scale, and the level of agricultural mechanization. The basis for choosing education level as a group is that digital finance is a new concept, and professional farmers with different levels of education will show different levels of acceptance and difficulty in using digital finance [50]. The basis for choosing farmland management scale as a group is that the significant differences in the financing needs of farmers with different management scales will affect the enthusiasm of farmers in participating in digital finance to a certain extent, and thus lead to discrepancies in the income-increasing effect of digital finance. The level of agricultural mechanization was chosen on the basis that the level of agricultural mechanization represents different agricultural productivity levels, and its impacts on farmers' incomes are different. In addition, we explored the impacts of different digital financial services on the income of professional farmers, which helps us to better understand the role of different digital financial services.

5.2.1. Grouped by Different Levels of Education

In this paper, according to the educational level of the household head, the rural households are divided into three groups: low education level (primary school and below), middle education level (junior high school), and high education level (high school and above). This paper used the 2SLS model to estimate, and Table 8 reports the specific empirical results. It can be seen from Table 8 that the involvement in digital finance of professional farmers with a high level of education has a significant positive impact on their total household income. Still, the effects of the involvement in digital finance of professional farmers with low and medium education levels on their total household income need to be made more evident. Since digital finance is new, farmers' education level also affects their acceptance and use of it to a certain extent. For farmers with a high level of education, on the one hand, they can more easily purchase wealth management products that meet their own needs from the digital financial market to obtain corresponding property income. In the digital financial market, credit products that meet production needs are found to increase investment in agricultural production and increase agricultural income levels. Therefore, digital finance has a more significant role in promoting the total income of this group of households [51].

Table 8. The impact of digital finance on the income of professional farmers with different education levels and different farmland management scales.

Variable	Different Levels of Education			Different Farmland Management Scales			
	Low	Middle	High	Small	Small and Medium	Medium and Large	Large
Digital finance involvement	0.544 (0.396)	0.753 (0.839)	1.167 ** (0.568)	0.730 (0.872)	0.742 ** (0.376)	0.857 (0.840)	0.953 ** (0.480)
The first stage estimation—whether to participate in digital finance							
The average level of digital financial involvement in the same age group in the same county	0.850 *** (0.219)	0.333 ** (0.142)	0.812 *** (0.191)	0.599 ** (0.263)	0.895 *** (0.228)	0.685 *** (0.231)	0.947 *** (0.228)
Cragg–Donald Wald F-statistic	17.491	5.435	18.444	6.743	19.948	10.529	18.313
Control variable	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
Observations	395	488	147	248	236	252	294

Note: *** and ** indicate that the estimated coefficients are significant at 5% and 10%, respectively; the values in brackets are robust standard errors. Data source: Calculated by the software STATA 14.0.

5.2.2. Grouped by Different Farmland Management Scales

According to the quartiles of farmland management scale, this paper divided the sample farmers into four groups: small scale, small and medium scale, medium and large scale, and large scale. The 2SLS model is used for estimation, and the specific regression results are shown in Table 8. We can see in Table 8 that digital financial involvement has a significant positive impact on the total income of professional farmers with small and medium-scale operations and large-scale operations, but has no significant effect on the total income of professional farmers with small and medium-sized operations. Judging from the impact coefficient, digital finance has a more substantial effect on the total income of professional farmers with a large scale of operations. The possible reason is that, compared with professional farmers with other scales, large-scale professional farmers have a higher demand for capital. With the continuous improvement of the farmland mortgage loan system, land has become available for mortgage loans. "Living assets" effectively reduce credit risk, so large-scale professional farmers can more easily obtain credit support when participating in the digital financial market. In addition, the increase in production investment funds will help to optimize the allocation of factors, thereby increasing the total income of professional farmers' families [8].

5.2.3. Grouped by Different Levels of Agricultural Mechanization

In this paper, 0.33 and 0.65 quantiles were taken as the cutoff points, and the whole sample was divided into low level of agricultural mechanization, medium level of agricultural mechanization, and high level of agricultural mechanization according to the level of agricultural mechanization. On this basis, the 2SLS model is used for analysis, and the regression results are shown in Table 9. It can be seen from Table 9 that digital finance only has a significant positive impact on the income of professional farmers in the high level of agricultural mechanization group, while the impact on the income of professional farmers in the low and medium levels of agricultural mechanization groups is not significant. From the perspective of the impact coefficient, with the improvement of agricultural mechanization, the promoting effect of digital finance on the income of professional farmers is gradually increasing. The possible reason is that the higher the level of agricultural mechanization, the more productive the farmer is, and the easier it is for them to increase their income. Driven by the goal of maximizing income, farmers will be more inclined to access the credit funds needed for production through digital financial structures to optimize the allocation of production factors and promote income growth.

Table 9. The impact of digital finance on the income of professional farmers with different levels of agricultural mechanization.

Variable	Low Level of Agricultural Mechanization	Medium Level of Agricultural Mechanization	High Level of Agricultural Mechanization
Digital finance involvement	0.402 (1.124)	0.979 (0.709)	1.091 ** (0.452)
	The first stage estimation—whether to participate in digital finance		
The average level of digital financial involvement in the same age group in the same county	0.422 * (0.248)	0.518 *** (0.191)	0.792 *** (0.187)
Cragg–Donald Wald F-statistic	3.526	8.219	19.007
Control variable	Controlled	Controlled	Controlled
Observations	338	331	361

Note: ***, ** and * indicate that the estimated coefficients are significant at 1%, 5%, and 10%, respectively; the values in brackets are robust standard errors. Data source: Calculated by the software STATA 14.0.

5.2.4. Grouped by Different Digital Financial Services

Table 10 reports on the impacts of different digital financial services on professional farmers' income. As can be seen from Table 10, mobile payments and digital credit all have a significant positive impact on professional farmers' income. The impact of digital wealth management on professional farmers' income is positive but not significant. This means that professional farmers can impact their income mainly through mobile payment services and digital credit services, while the impact of digital wealth management on professional farmers' income has not yet been elucidated. This also reflects that digital wealth management services will be key to the business of digital financial institutions in rural areas in the future, which can provide new ways for farmers to increase their income.

Table 10. The impacts of different digital financial services on professional farmers' income.

Variable	(1)	(2)	(3)
Mobile payment	0.997 ** (0.412)		
Digital credit		1.880 ** (0.787)	
Digital wealth management			4.083 (2.593)
The first stage estimation—whether to participate in digital finance			
The average level of digital financial involvement in the same age group in the same county	0.524 *** (0.118)	0.278 *** (0.061)	0.128 * (0.070)
Cragg–Donald Wald F-statistic	23.434	17.609	3.431
Durbin–Wu–Hausman test	4.038 **	4.498 **	5.800 **
Control variable	Controlled	Controlled	Controlled
Observations	338	331	361

Note: ***, ** and * indicate that the estimated coefficients are significant at 1%, 5%, and 10%, respectively; the values in brackets are robust standard errors. Data source: Calculated by the software STATA 14.0.

6. Discussion

The existing findings on the impact of digital finance on farmers' income levels and income structure are still controversial. This paper responds to this issue by taking professional farmers in the main apple-producing areas as the research object. It is found that digital finance has a certain impact on professional farmers' income growth; however, it is not achieved by directly increasing the property income and transfer income of professional farmers but through indirect paths. In particular, digital finance has an impact on total household income by promoting productive investment to increase agricultural income, and by promoting household entrepreneurship to increase household self-employment business income. In addition, the impact of digital finance on the salary income of professional farmers is negative but not significant. Compared with existing studies, the biggest difference in this paper is that there are studies that analyze farmers as a whole and conclude that digital finance increases non-farm income but decreases agricultural income. In contrast, this paper focuses on professional farmers, and concludes that digital finance increases agricultural income but decreases non-farm income. Although the conclusions in this paper seem to diverge from the prevailing viewpoint, they do not conflict. Along with the acceleration of industrialization and urbanization, it is an inevitable trend that agricultural laborers move to non-farm industries. Those who remain in rural areas are the new agricultural business subjects represented by professional farmers, who are the backbone of rural revitalization and the main force of future agricultural development. The penetration of digital finance in rural areas can provide strong support for the development of production and management activities of professional farmers, thereby contributing to the full revitalization of rural areas. Therefore, the conclusion of this paper has important policy implications.

The limitations of this paper mainly include the following: First, due to data availability, the cross-sectional data used in this paper cannot be used to analyze the dynamic impact of digital finance on farmers' income. The second is that this article only took professional apple households as the research object to explore. Then, we must consider if there is any difference in the impact effects and impact paths of digital finance on other types of new agricultural business entities, such as family farms and cooperatives. Third, what is the difference between the impacts of digital finance on farmers' incomes in developed and developing countries? Fourth, can digital finance promote intergenerational income mobility? What are the effects of digital finance on intergenerational income mobility between regions, ethnic groups, and urban and rural areas? These are the focus of future research.

7. Conclusions and Enlightenment

We used 1030 professional apple growers in Shaanxi Province, China, as the research object, and empirically tested the influence of digital financial involvement on professional farmers' income using the OLS model, 2SLS model, and other methods. The research results show that digital finance has a specific positive impact on the growth of total household income, but not through a direct mechanism (that is, digital finance cannot directly increase property income and transfer income), and rather through an indirect mechanism. Specifically, the findings are as follows: first, digital finance can increase agricultural income by promoting productive investment; second, digital finance can increase household self-employed industrial and commercial income by promoting farmers' family entrepreneurship. Heterogeneity analysis showed that the involvement of highly educated professional farmers in digital finance could significantly increase their household income. Still, the impacts of low-educated and middle-educated professional farmers' involvement in digital finance on their total household income are insignificant. The involvement of small, medium-sized, and large-scale professional farmers in digital finance has a significant positive impact on their total household income. Still, the effect of small and medium-sized professional farmers' involvement in digital finance on their total household income is insignificant. From the perspective of the impact coefficient, digital financial involvement has a more substantial promoting effect on professional farmers with a large scale of operation. Digital finance has a significant positive impact on the income of professional farmers in the high level of agricultural mechanization group, while the impact on the income of professional farmers in the low and medium levels of agricultural mechanization groups is not significant. From the perspective of the impact coefficient, digital finance has the greatest effect on the income of professional farmers with a high level of agricultural mechanization. Mobile payments and digital credit have a significant positive impact on professional farmers' income, but the income-generating effect of digital wealth management has not yet been elucidated.

Based on the above conclusions, we draw the following implications. First, we should increase the construction of digital infrastructure, such as the internet, in rural areas to effectively promote the rapid development of digital finance in rural areas, fully release the vitality of digital finance, and make digital finance a booster of revitalization in rural areas. Second, agriculture-related financial institutions should continue to enrich digital financial products and services to effectively meet the financial needs of different farmers, facilitate their production, operation, and investment, and provide strong support for farmers to continue to increase their income. Third, attention should be paid to improving the level of human capital in rural areas. From the perspective of digital financial services, the proportion of mobile payments is the highest, and the ratio of digital credit and digital wealth management is relatively low. An important reason is that the level of human capital in rural areas is low, and using digital financial services requires specific financial knowledge. As a result, difficulties are often present, especially among the poorly educated and older peasants. Therefore, we can publicize and popularize relevant digital financial knowledge to farmers through lectures and other methods to improve their financial literacy; on the other hand, we can train farmers in the skills of using financial technology apps so that farmers can better share the dividends of digital financial development. Fourth, as the main force of China's modern agricultural development, new-type agricultural management entities have higher demands for funds than ordinary farmers. The credit constraints they face will seriously restrict their development and growth. Therefore, we should pay attention to the supporting role of digital finance in cultivating new agricultural business entities such as large professional households, continuously optimize the rural financial supply system, and effectively solve problems such as financing difficulties for new agricultural business entities, thereby promoting the high-quality development of new agricultural business entities. Fifth, the success of farmers' entrepreneurship is related to the prosperity of the rural economy and the development of rural society. Given the limited accumulation of farmers' capital, there is generally a financial threshold to their entrepreneurship. Therefore, with the help of the rapid growth of digital finance, efforts should be made to solve the financial problems restricting farmers' entrepreneurship so as to effectively enhance farmers' enthusiasm for entrepreneurship and fully stimulate the vitality of the rural economy.

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