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Article

Does Agricultural Digital Transformation Improve Access to Agricultural Productive Credit for Farmers?

Mingdong Zhou ¹, Wenqin Guo ² and Lei Zhang ^{1,3,*}

- ¹ College of Economics and Management, Suqian University, 223800 Suqian, China
- ² Suyin Financial Leasing Co., Ltd., 210005 Nanjing, China
- ³ School of Finance, Nanjing University of Finance and Economics, 210023 Nanjing, China
- * Correspondence: nauzhanglei@163.com

Abstract

This paper draws on survey data from 585 family farms in Jiangsu Province, China, in 2023. It endeavors to examine how farmers’ utilization of information and communication technologies (ICT) in agricultural production and management affects their access to agricultural production credit. The results demonstrate that farmers who apply ICT more comprehensively in agricultural production and management are more inclined to obtain agricultural production credit. Intriguingly, these outcomes persist resilient even when taking into account selection bias and endogeneity issues. In terms of transmission mechanisms, agricultural digital transformation can facilitate farmers’ access to agricultural production credit. Specifically, it does so by reducing the credit transaction costs related to bank loans and enhancing the efficiency of agricultural resource allocation. Furthermore, the heterogeneity analysis reveals that agricultural digital transformation is more conducive for smallholder farmers to acquire agricultural production credit from large banks. Finally, it is evident that the application of ICT in areas such as agricultural product sales and the management of agricultural digital equipment is more beneficial for farmers in attaining agricultural production credit.

Keywords: ICT adoption; agricultural productive credit; credit transaction cost; agricultural resource allocation

JEL Classification: G51; O33; Q14

1. Introduction

The development of agricultural credit is crucial for promoting the sustainable growth of agriculture in developing countries and enhancing the efficiency of agricultural resource allocation (Chen et al., 2022; Latief et al., 2023; Nakano et al., 2020). In nations like China, where the agricultural model is transitioning from small-scale, fragmented farming to large-scale, intensive cultivation, substantial agricultural credit is required to support this transformation. However, large-scale farmers, who are becoming the primary contributors to China’s agricultural sector, continue to face significant credit constraints. According to the 2020 “China Rural Policy and Reform Statistical Annual Report,” family farms managed 29.32% of the national household-contracted farmland that year, yet they received only 0.045% of the total national loans allocated to agriculture, forestry, animal husbandry, and fisheries. Thus, advancing agricultural credit development in populous countries with scarce agricultural resources, such as China, is pivotal for ensuring global food security and sustainable agricultural development.

Existing research on agricultural credit access has predominantly explored factors such as the caste system, agricultural insurance, farmer household human capital, farmland size, and agricultural property rights reforms (Kumar et al., 2013; Akpan et al., 2013; Mishra et al., 2021). For instance, Kumar et al. (2013) found that in India, credit cooperative bank loans are more likely to

favor upper-caste farmers compared to commercial banks, indicating caste-based biases in credit allocation. Akpan et al. (2013) examined the demand for and access to agricultural credit among poultry farmers in Akwa Ibom State, Nigeria, revealing that factors such as farmers' education levels and loan acquisition experience significantly influence credit access. Kvartiuk et al. (2021) assessed the impact of Kazakhstan's 2003-2005 agricultural land reform on the agricultural credit market, finding that the reform did not promote the use of land as collateral. Cheng et al. (2021) reached similar conclusions regarding China's agricultural property rights reform. Kehinde et al. (2023) found that loan experience significantly affects microfinance access among fish farmers in Osun State, Nigeria. Mishra et al. (2021) conducted a randomized controlled trial in northern Ghana, demonstrating that bundling index insurance with loans increases the likelihood of farmers receiving credit.

With the increasing prevalence of the Internet, scholars have recognized the significant impact of digital technology on farmers' access to credit. For example, Suri et al. (2021) studied Kenyan farmers and found that digital banking technology facilitates access to small-amount credit and enhances household resilience to shocks. Riley et al. (2018) also focused on Kenya, revealing that mobile payments help farmers access external funds, thereby mitigating the impact of flood disasters on consumption. Ma et al. (2023) studied Chinese farmers and found that the use of ICT increases the probability of obtaining credit by 12.8%. However, existing research predominantly examines the impact of financial institutions' use of digital technology on credit access, with limited studies exploring the effects of farmers' use of the Internet or mobile phones on credit. Few studies have investigated the relationship between ICT use in agricultural production and business operations and farmers' access to credit. One notable exception is Agyekumhene et al. (2018), who found that establishing a digital platform for corn supply chains in Ghana facilitates credit access for downstream farmers. However, their study was a case analysis and lacked empirical validation.

The main objective of this study is to analyze the relationship between the application of information and communication technology (ICT) in agricultural production and management and farmers' access to agricultural credit, using survey data collected by the research team in 2023 from 585 household farming households in Jiangsu Province. Furthermore, this study also explores the mechanisms by which ICT influences farmers' access to agricultural credit.

This article contributes to the literature in several ways. First, it analyzes the impact of ICT technology on agricultural credit acquisition within production and operational contexts. Existing research typically focuses on the effects of ICT technologies such as the Internet or mobile phones on credit access (Ma et al., 2023), without considering the impact of different ICT usage scenarios. Research indicates that varying ICT usage scenarios affect credit assessment differently (Berg et al., 2020). Thus, the influence of ICT on agricultural production and operations differs from its impact on credit access. Second, unlike studies that focus on the total credit scale obtained by farmers (Riley et al., 2018; Ma et al., 2023), this article emphasizes agricultural productive loans. In developing countries, agricultural productive loans often benefit from tax incentives or financial subsidies (Kannan et al., 2011; Zhang et al., 2023). Consequently, factors affecting overall credit scale differ from those impacting agricultural productive credit. Third, this study explores the impact of ICT technology on farmers' repayment ability, a dimension often overlooked in existing research that focuses primarily on transaction costs (Suri et al., 2021; Asongu et al., 2019). We find that ICT technology positively influences credit access by enhancing resource allocation efficiency. Fourth, this article evaluates the different impacts of using ICT technology on the acquisition of agricultural productive loans at different stages of agricultural production and operation, and provides insights into which ICT technologies are most effective in improving the acquisition of agricultural productive loans.

The remainder of this article is structured as follows: Section 2 develops hypotheses based on relevant literature and theory. Section 3 introduces variables related to digital transformation in agriculture and agricultural productive credit, along with the empirical models and data used. Section 4 presents quantitative results exploring the impact of agricultural digital transformation on

agricultural productive credit access. Section 5 analyzes the mechanisms through which agricultural digital transformation affects agricultural productive credit access and evaluates the heterogeneous impacts of ICT technology use across different agricultural management stages. Finally, the article concludes with a discussion of the research findings and their implications.

2. Theoretical Analysis and Research Hypotheses

Agricultural digital transformation entails the incorporation of digital technologies, including the mobile Internet, blockchain, and the Internet of Things, into agricultural production and operations (Ozdogan et al., 2017). This transformation can boost farmers' access to agricultural productive credit through two mechanisms: reducing credit transaction costs and improving the efficiency of agricultural resource allocation.

2.1. *The Mechanism of Transaction Cost Mechanism*

Transaction cost theory posits that information asymmetry engenders a plethora of costs. These costs span those associated with the acquisition and search for market information, the negotiation and decision-making processes regarding contracts, as well as the monitoring and enforcement of contracts subsequent to agreement formation (Coase et al., 2013). High transaction costs are a pivotal factor contributing to the prevalence of credit constraints or rationing among farmers (Pingali et al., 2005).

The digital transformation of agriculture has the potential to attenuate credit transaction costs through digital modalities. Examples include the Internet-enabled sales of agricultural products and the employment of agricultural management ICT software. Digital platforms, such as e-commerce and online live-streaming sales, facilitate the conversion of qualitative data—such as farmers' product sales volumes, unit prices, and product reputations—into quantitative information by means of digital tools. Empirical research has demonstrated that advancements in financial technology empower financial institutions to capitalize on borrowers' digital footprints as a vital component in credit assessment (Berg et al., 2020). Consequently, the digital transformation of agriculture enables banks and other financial institutions to curtail the costs incurred in information collection preceding lending. Additionally, physical distance has long been acknowledged as a formidable barrier to information access for financial institutions (Agarwal et al., 2010). ICT tools, such as remote monitoring and satellite remote sensing, play a crucial role in surmounting these barriers by enabling seamless remote monitoring and communication. Thus, agricultural digital transformation effectively reduces the post-loan supervision costs for financial institutions.

In essence, the digital transformation of agriculture can lower the transaction costs associated with agricultural credit contracts, thereby enhancing farmers' access to agricultural productive credit.

2.2. *The Mechanism of Resource Allocation Mechanism*

Digital transformation not only bolsters the accessibility of agricultural credit by reducing transaction costs but also enhances credit access via more efficient agricultural resource allocation.

From the vantage point of profitability, investment in ICT tools for e-commerce and agricultural information management has the potential to expand market frontiers and boost farmers' sales revenue (Sheng et al., 2020). ICT technologies, including online social networking and search tools, lower the costs associated with market development, enhance supply-demand matching efficiency, and elevate profitability. Concerning the stability of profitability, agricultural information management systems assist in alleviating the impacts of price volatility and uncertain business environments on farmers' profits. Owing to lags in information dissemination, agricultural product prices can exert a destabilizing influence on farmers' income. ICT technologies, such as big data and Internet communications, enable farmers to circumvent unstable sales and mitigate the impact of obsolete price information on business decisions (Mittal et al., 2012). Moreover, the utilization of drones and smart agricultural machinery further decreases labor intensity and management costs

(Hou et al., 2019). Thus, agricultural digital transformation augments profitability through optimized agricultural resource allocation (Oyinbo et al., 2022), thereby enhancing the accessibility of agricultural productive credit.

Based on the foregoing analysis, this article posits the following hypotheses:

Hypothesis 1: *Agricultural digital transformation improves farmers' access to agricultural productive credit.*

Hypothesis 2: *Agricultural digital transformation enhances the availability of agricultural productive credit by reducing transaction costs.*

Hypothesis 3: *Agricultural digital transformation increases the availability of agricultural productive credit by improving resource allocation.*

3. Materials and Methods

3.1. Data Sources

The data for this study are derived from a 2023 questionnaire survey administered across 585 family farms in seven prefecture—level cities in Jiangsu Province, China. This survey spans the northern, central, and southern regions of Jiangsu. The northern region of Jiangsu, lying north of the Yellow River, is classified as part of northern China. Central Jiangsu and some northern areas, situated between the Yangtze River and the Yellow River, are categorized as central China. The southern region of Jiangsu, located south of the Yangtze River, is part of southern China. In terms of topography, the northern part of Jiangsu features hilly terrain and is mainly planted with wheat and corn, whereas the southern part is a plain area where rice is predominantly cultivated. Thus, the survey's coverage in terms of both climate and topography is highly representative. The questionnaire encompasses multi—dimensional information, covering basic farm details, agricultural digital transformation, and access to agricultural productive credit, thereby enabling a comprehensive evaluation of the impact of digital transformation on farmers' access to agricultural productive credit.

3.2. Variable Selection

3.2.1. Explained Variable

Existing literature on agricultural productive credit typically measures it using questions such as “whether agricultural productive credit was obtained” and “the scale of agricultural productive credit” (Agbodji et al., 2021; Moreira—Dantas et al., 2023). To assess the marginal effect of agricultural digital transformation on farmers' access to agricultural productive credit, this study follows the approaches in existing research (Moreira—Dantas et al., 2023) and adopts the “agricultural productive credit access scale” (Loan_ag) as the measure of agricultural productive credit access. Meanwhile, referring to existing literature (Ma et al., 2023), we also use the “total scale of credit obtained by households” (Loan_total) as an alternative variable for robustness testing.

3.2.2. Core Explanatory Variables

Digital transformation in agriculture principally pertains to the intensity of the utilization of digital technology services or intelligent agricultural machinery in agricultural production and management (Smidt et al., 2022). Drawing on existing research (Drewry et al., 2019), this paper categorizes agricultural digital transformation into three dimensions according to the agricultural production and management process: digitalization in the pre—production preparation stage, digitalization in the production stage, and digitalization in the post—production sales stage.

As presented in Table 1, these dimensions are manifested by five specific indicators. The indices are predominantly calculated using the equal—weight method and the entropy—weight method. Given that all indicators share the same measurement scale and value range, we employ the equal—weight method to compute the degree of agricultural digital transformation. Simultaneously, to

circumvent subjective bias, we will also utilize the entropy – weight method for robustness checks. Details are provided in Table 1.

Table 1. Evaluation Dimensions of Agricultural Digital Transformation.

Dimension	Specific measurement	Variable Description
Prenatal preparation stage	Digital purchase of agricultural production materials	If yes, the value is 1; If not, the value is 0
Production stage	Digitalization of agricultural production equipment	If yes, the value is 1; If not, the value is 0
	Agricultural technical assistance digitalization	If yes, the value is 1; If not, the value is 0
	Digitization of agricultural technology exchange	If yes, the value is 1; If not, the value is 0
Postpartum sales stage	Digital sales of agricultural products	If yes, the value is 1; If not, the value is 0

3.2.3. Mechanism Variables

The mechanisms to be verified in this paper consist of the transaction – cost mechanism and the resource – allocation mechanism.

For the transaction – cost mechanism, drawing on existing research (Agarwal et al., 2010), the variable required is “the distance between the farmer and the bank”. If this distance exceeds the sample median, the value is set to 1; otherwise, it is set to 0.

Regarding the resource – allocation mechanism, referring to existing research (Allen et al., 2009), the variable needed is “agricultural income per acre”. This is calculated as the total household agricultural income divided by the total area of the household’s cultivated land.

3.2.4. Control Variables

Control variables incorporate characteristics at the household – head and family levels, as these can influence farmers’ demand for and access to agricultural credit.

At the household – head level, the variables include “age, sex, and education level”. For “sex”, a value of 1 represents male and 0 represents female. The education level (Edu) is categorized as follows: 1 for illiterate, 2 for primary – school education, 3 for junior – high – school education, 4 for senior – high – school education, 5 for junior – college education, 6 for a bachelor’s degree, and 7 for a postgraduate degree.

At the family level, the variables include the cultivated – land area (Land_plant), total non – agricultural income (Inc_noag), total family agricultural income (Sale_ag), and whether agricultural insurance was purchased (Agri_insurance). All these data were collected via a questionnaire survey. Table 2 presents the explanatory and descriptive statistics for all variables.

Table 2. Variable Description.

Variable	Variable Description	Obs	Mean	Std.
Dependent variables				
Loan_ag	Total agricultural productive borrowings in 2022 (10,000 yuan)	585	36.83	79.86
Core Explanatory Variable				
Agri_ict	Agricultural digital transformation level. The index ranges from 0 to 1.	585	0.645	0.230
Mechanism variables				

Bank_distance	Whether or not the distance from the household to the bank exceed the sample median (yes = 1; no = 0)	585	0.354	0.479
Farm_roe	Agricultural sales revenue divided by total cultivated land area (ten thousand yuan/mu)	560	0.644	1.559
Control Variables				
Age	Age of head of household (years)	584	50.45	9.428
Sex	Gender of household head (male=1; female=0)	585	0.884	0.321
Edu	Educational level of the head of household (illiteracy=1; primary school=2; junior high school=3; high school=4; college=5; bachelor's degree=6; master's degree=7)	585	10.10	3.224
Land_plant	Total area of cultivated land (mu)	560	347.1	433.7
Inc_noag	Total household income excluding agriculture in 2022 (10,000 yuan)	585	13.30	33.13
Sale_ag	Total agricultural sales revenue in 2022 (10,000 yuan)	585	117.4	233.2
Agri_insurance	Whether or not purchase agricultural insurance (yes = 1; no = 0)	585	0.988	0.109

3.3. Empirical Model

To verify whether agricultural digital transformation positively impacts farmers’ access to agricultural productive credit, this study constructs a linear regression model for empirical analysis.

$$Loan_a\ g_i = \beta_0 + \beta_1 Agri_i\ ct_i + \beta_2 Control_var_i + \varepsilon_i$$

(1)

In the above formula, *Loan_ag_i* represents the scale of agricultural productive loans obtained by the *i* farmer, and *Agri_ict_i* represents whether the *i* farmer uses ICT technology in the five aspects of “agricultural product sales, purchase of production materials, agricultural information software, agricultural technology online services, and technology exchange”. *Control_var_i* represents a series of control variables. *ε_i* represents the random error term. If the coefficient *β₁* is significantly positive, it means that agricultural digital transformation is conducive to improving the availability of agricultural productive credit for farmers.

4. Results

4.1. Regression Analysis

To evaluate whether the digital transformation of agriculture exerts a positive influence on farmers’ access to agricultural production credit, this paper employs a linear regression model. In the process of empirical analysis, control variables are added step—by—step. The specific empirical results are presented in Table 3.

Table 3. Agricultural Digital Transformation and Agricultural Productive Credit Availability.

Variables	(1)	(2)	(3)
	loan_ag	loan_ag	loan_ag
agri_ict	49.356** (20.485)	44.700** (21.024)	42.210** (20.881)
age		0.066 (0.557)	0.739 (0.552)
sex		-2.787 (14.923)	-5.554 (14.979)
edu		2.393	2.876*

		(1.612)	(1.586)
land_plant			0.073***
			(0.012)
inc_noag			0.181
			(0.140)
sale_ag			0.051**
			(0.023)
agri_insurance			-9.864
			(41.638)
Constant	5.106	-16.851	-75.456
	(14.022)	(42.823)	(58.298)
Observations	585	584	559
R-squared	0.010	0.014	0.130

Significant at 10% (*), 5% (**), 1% (***) levels.

As presented in the empirical results in column 1 of Table 3, the factor of agricultural digital transformation exerts a significantly positive impact on the scale of agricultural production credit at the 5% significance level. This implies that agricultural digital transformation is conducive to farmers obtaining more agricultural production credit. Moreover, as indicated by the empirical results in columns 2 and 3 of Table 3, this finding remains positively significant at the 5% significance level even after incorporating control variables at the household—head and family levels. This consistency demonstrates the robustness of the conclusion that agricultural digital transformation improves farmers’ access to agricultural production credit. Consequently, Hypothesis 1 is verified.

Concerning the control variables, the scale of cultivated—land management significantly impacts access to agricultural production credit. For each additional mu (approximately 0.16 acres) of cultivated land, the amount of agricultural production loans rises by 730 yuan. This effect likely stems from the economies of scale in agricultural production, which boosts profitability and thereby increases financial institutions’ propensity to lend. Additionally, household income also has a positive influence on access to agricultural production credit. For every 10,000—yuan increase in household income, the amount of agricultural loans increases by 510 yuan. This suggests that the profitability of agricultural production affects the scale of credit access for farmers.

4.2. Robustness Analysis

4.2.1. Replace Empirical Model

In the aforementioned study, we predominantly utilized a linear regression model to investigate the impact of agricultural digital transformation on farmers’ access to agricultural production credit. Linear regression models typically necessitate the explained variable to be continuous and have an unrestricted range of values. Consequently, to circumvent potential truncation problems associated with agricultural production credit, this study further deploys a Tobit model for robustness testing. The specific empirical results are presented in column 1 of Table 4.

Table 4. Agricultural Digital Transformation and Agricultural Productive Credit Availability: Robustness Analysis.

Variables	(1)	(2)	(3)
	loan_ag	loan_ag	loan_total
agri_ict	70.983** (35.315)		47.977*** (13.756)
digital_agriculte		34.204** (16.090)	
Individual control variables	YES	YES	YES
Family control variables	YES	YES	YES

Constant	-144.952 (98.888)	-63.319 (56.785)	-53.776 (38.405)
Observations	559	559	559
R-squared		0.131	0.218

Significant at 10% (*), 5% (**), 1% (***) levels.

4.2.2. Replace Explanatory Variables

In the aforementioned study, we predominantly employed the agricultural digital—transformation index calculated via the equal—weight method as the explanatory variable. The equal—weight method assumes that all variables carry the same importance; however, it readily overlooks the disparities and fluctuations among variables. Consequently, to circumvent the potential measurement bias stemming from the equal—weight method, we further utilized the entropy—weighted method to compute the agricultural digital—transformation index and carried out a robustness test. The specific empirical results are presented in column 2 of Table 4.

4.2.3. Replace the Explained Variable

In the aforementioned study, we predominantly utilized the agricultural production loans farmers obtained as the dependent variable. Nevertheless, as credit providers like banks find it challenging to monitor the actual utilization of loans by farmers, farmers might also invest non—agricultural loans in agricultural production and management (Fecke et al., 2016). Consequently, to circumvent the potential measurement bias arising from using agricultural production loans as the dependent variable, we further employed the total credit amount farmers obtained as the dependent variable for robustness testing. The specific empirical results are presented in column 3 of Table 4.

The empirical results in column 1 of Table 4 demonstrate that, when applying the Tobit model, the impact of agricultural digital transformation on the scale of agricultural production credit remains positively significant at the 5% significance level. This indicates the robustness of the basic regression results. Simultaneously, the empirical findings in column 2 of Table 4 reveal that, upon calculating the agricultural digital transformation index using the entropy—weighting method, the impact of agricultural digital transformation factors on the scale of agricultural production credit does not change significantly. Finally, the empirical results in column 3 of Table 4 show that, with the total credit amount obtained by farmers as the explained variable, the impact of agricultural digital transformation on the scale of agricultural production credit is also positively significant. Overall, the conclusion that agricultural digital transformation can enhance farmers’ access to agricultural production credit is reliable.

4.3. Endogeneity Analysis

4.3.1. Testing for Reverse Causality

As farmers might allocate agricultural production credit to purchase agricultural digital—technology services or smart machinery, an endogeneity problem of mutual causation could occur between agricultural digital transformation and agricultural production credit. In light of this, we utilize the “mean of agricultural digital transformation among farmers in the same village” (dig_village) as an instrumental variable for agricultural digital transformation. Existing literature indicates that agricultural digital transformation has a peer effect (Xie et al., 2021; Klerkx et al., 2019). Consequently, agricultural digital transformation among farmers in the same village is correlated with that of individual farmers, which adheres to the relevance principle of instrumental—variable selection. Simultaneously, agricultural digital transformation among farmers in the same village does not directly influence farmers’ agricultural production credit decisions (Tang et al., 2011), which complies with the exogeneity principle of instrumental—variable selection. Based on these considerations, we employ a two—stage least—squares (2SLS) model for empirical testing. The specific results are presented in Table 5.

Table 5. Agricultural Digital Transformation and Agricultural Productive Credit Availability: Endogeneity Analysis.

Variables	(1)	(2)
	Loan_ag	Loan_ag
Agri_ict	50.456** (23.885)	41.246* (24.541)
Individual control variables	NO	YES
Family control variables	NO	YES
Constant	4.397 (16.101)	-74.697 (58.746)
Anderson canon. Corr. LM statistic	428.848 (0.000)	398.191 (0.000)
Cragg-Donald Wald F statistic	1601.117	1361.897
Sargan statistic	0.000	0.000
Observations	585	559
R-squared	0.010	0.130

Significant at 10% (*), 5% (**), 1% (***) levels.

The empirical results in column 1 of Table 5 demonstrate that the LM statistic of Anderson’s canonical correlation test is 428.848, significant at the 1% significance level, suggesting that there is no weak—instrumental—variable problem. Moreover, the Cragg—Donald—Wald F statistic is 1601.117 (substantially greater than 10), and the p-value of the Sargan statistic is 0.000, verifying that the instrumental variables do not give rise to weak—instrumental—variable or over—identification problems. When using the “mean of agricultural digital transformation among farmers in the same village” as the instrumental variable, the impact of agricultural digital transformation on farmers’ agricultural production credit remains significantly positive. Finally, the empirical results in column 2 of Table 5 show that, after incorporating control variables at the household—head and family levels, the conclusion that agricultural digital transformation promotes farmers’ access to agricultural production credit remains robust.

4.3.2. Testing for Omitted Variables

Referring to existing literature (Altonji et al., 2005), this paper uses a coefficient stability sensitivity test to assess the impact of omitted variables on core explanatory variables. First, two regression models are designed: one including constrained control variables and the other including fully controlled variables. Second, through regression analysis, the coefficients of the core explanatory variables in the constrained control variable model are calculated as β_r , and the coefficients in the fully controlled variable model are calculated as β_f . Finally, the rate of change of

the core explanatory variable coefficients($Ratio = \left| \frac{\beta_f}{(\beta_f - \beta_r)} \right|$) between the constrained and fully controlled variable models is calculated. A larger rate of change indicates that the core explanatory variables are less affected by the omitted variable problem.

Based on the foregoing principles, this paper devises two sets of omitted—variable evaluation models. In the first set of omitted—variable evaluation models, the restricted—control—variable model encompasses only the core explanatory variables, whereas the fully—controlled—variable model incorporates both the core explanatory variables and individual—level control variables. In the second set of omitted—variable evaluation models, the restricted—control—variable model includes both the core explanatory variables and individual—level control variables, while the fully—controlled—variable model comprises both the core explanatory variables and individual—and family—level control variables.

As is evident from the ratio in the last row of the empirical results in columns 1 and 2 of Table 6, in the first group of omitted – variable evaluation models, the estimation results will exhibit bias due to omitted variables only when the potential impact of the omitted variables on the model is at least 9.601 times that of the control variables in the existing model. In the second group of omitted – variable evaluation models, the rate of change of the core explanatory variable coefficients between the control – variable model and the fully – controlled – variable model is also 16.952. This suggests that the empirical analysis of the relationship between agricultural digital transformation and farmers’ agricultural production credit is minimally affected by the omitted – variable problem, and the estimation results of the benchmark regression in this paper are relatively robust.

Table 6. Agricultural Digital Transformation and Agricultural Productive Credit Availability: omitted variable problem test.

Variables	(1)	(2)	(3)	(4)
	Group1		Group2	
	loan_ag	loan_ag	loan_ag	loan_ag
agri_ict	49.356** (20.485)	44.700** (21.024)	44.700** (21.024)	42.210** (20.881)
Individual control variables	NO	YES	YES	YES
Family control variables	NO	NO	NO	YES
Constant	5.106 (14.022)	-16.851 (42.823)	-16.851 (42.823)	-75.456 (58.298)
Observations	585	584	584	559
R-squared	0.010	0.014	0.014	0.130
Ratio	9.601		16.952	

4.4. Mechanism Analysis

The foregoing analysis confirms that agricultural digital transformation can enhance farmers’ access to agricultural production credit. Nevertheless, whether agricultural digital transformation can further improve farmers’ access to agricultural production credit via credit – transaction – cost mechanisms and agricultural – resource – allocation mechanisms remains to be validated.

Regarding the transaction – cost mechanism, this paper primarily verifies it by comparing the marginal coefficients of agricultural digital transformation in the two subsamples of “far from banks” and “near banks”. Simultaneously, to enhance the robustness of the transaction – cost mechanism, this paper also employs an interaction – effect model.

As for the agricultural – resource – allocation mechanism, this paper mainly utilizes a mediation – effect model for verification. The mechanism analysis entails three steps:

- (1) Examining the influence of explanatory variables on the explained variable.
- (2) Examining the influence of explanatory variables on the mediating variable.
- (3) Incorporating both explanatory variables and mediating variables into the regression model.

4.4.1. Transaction Cost Mechanism

Existing research indicates that the distance between farmers and banks serves as an ideal indicator for gauging the transaction costs of farmer credit (Agarwal et al., 2010). The greater the distance between farmers and banks, the higher the transaction costs associated with pre – loan information gathering and post – loan monitoring. This paper partitions the sample into two subsamples – “far from banks” and “near banks” – based on the mean of the distance between farmers and banks, and computes the marginal impact of agricultural digital transformation on agricultural production credit for farmers in each subsample. The specific empirical results are presented in columns 1 and 2 of Table 7. Additionally, this paper incorporates the interaction between the distance between farmers and banks and factors related to agricultural digital transformation into

an interaction variable. By including this interaction variable in the regression analysis, the paper further validates whether the transaction—cost mechanism holds. The specific empirical results are shown in column 3 of Table 7.

Table 7. Agricultural Digital Transformation and Agricultural Productive Credit Availability: Transaction Cost Mechanism.

Variables	(1)	(2)	(3)
	loan_ag		
	Far from the bank	Close to the bank	Interactive variables
agri_ict	130.889*** (30.196)	16.898 (53.810)	50.617 (36.550)
agri_ict* bank_distance			54.224** (23.997)
Individual control variables	YES	YES	YES
Family control variables	YES	YES	YES
Constant	-156.144** (76.910)	-169.957 (170.098)	-168.667* (99.951)
Observations	197	362	559

Significant at 10% (*), 5% (**), 1% (***) levels.

The empirical results in columns 1 and 2 of Table 7 demonstrate that farmers located farther from banks benefit more from agricultural digital transformation and have easier access to agricultural credit compared to those nearer to banks. This indicates that agricultural digital transformation mitigates the transaction costs associated with pre—loan information gathering and post—loan monitoring stemming from geographical distance. Consequently, it can be concluded that agricultural digital transformation enhances the accessibility of agricultural production credit by reducing transaction costs. Additionally, the empirical results in column 3 of Table 7 show that, upon adding the interaction variable between the distance between farmers and banks and agricultural digital transformation, the interaction variable is positively significant at the 5% significance level. This further elucidates that agricultural digital transformation can improve farmers’ access to agricultural production credit through reducing the credit—transaction—cost mechanism. Thus, Hypothesis 2 is validated.

4.4.2. Agricultural Resource Allocation Mechanism

Although the foregoing text has demonstrated that agricultural digital transformation can facilitate farmers’ access to agricultural production credit by reducing transaction costs, it is equally crucial to verify whether it can improve farmers’ access to agricultural production credit by enhancing the resource—allocation mechanisms of family farms. Drawing on existing literature (Allen et al., 2009), this paper uses “agricultural income per acre” (Income_farm) as an indicator to measure the efficiency of agricultural resource allocation in family farms. On this basis, this paper employs a mediation—effect model to test the mechanism. The specific empirical results are presented in Table 8.

Table 8. Agricultural Digital Transformation and Agricultural Productive Credit Availability: Resource Allocation Mechanism.

Variables	(1)	(2)	(3)
	loan_ag	farm_roe	loan_ag
farm_roe			32.045** (12.723)
agri_ict	41.968** (20.957)	0.186*** (0.070)	35.992* (20.991)

Individual control variables	YES	YES	YES
Family control variables	YES	YES	YES
Constant	-69.434 (58.449)	0.732*** (0.195)	-92.882 (58.907)
Observations	559	559	559
R-squared	0.122	0.111	0.132

Significant at 10% (*), 5% (**), 1% (***) levels.

The empirical results in column 2 of Table 8 demonstrate that the factor of agricultural digital transformation exerts a significantly positive impact on per—mu agricultural income at the 1% significance level. This implies that agricultural digital transformation can enhance farmers’ capacity to allocate agricultural resources. The empirical results in column 3 of Table 8 show that, even when controlling for per—mu agricultural income, agricultural digital transformation still has a significantly positive impact on farmers’ agricultural production credit at the 5% significance level. Moreover, the Sobel test yields a Z—value of 1.832 and a P-value of 0.067, indicating that the mediating effect is valid. Agricultural digital transformation can improve farmers’ ability to allocate agricultural resources, thereby increasing the accessibility of agricultural production credit. Hypothesis 3 is thereby verified.

4.5. Heterogeneity Analysis

As illustrated above, agricultural digital transformation exerts a significant influence in facilitating farmers’ access to agricultural production credit. Nevertheless, it remains uncertain whether this impact differs across diverse credit providers, farmer scales, and digital—technology applications. Consequently, this paper will explore the heterogeneous impact of agricultural digital transformation on farmers’ access to agricultural production credit under varying credit providers, farmer scales, and digital—technology applications.

4.5.1. Heterogeneity by Bank Size

Information transmission necessitates not only that those seeking funding create a digital footprint through digital transformation, but also that those providing funding have tools like fintech to capture this digital footprint. Consequently, this paper classifies funding providers into two types according to whether agricultural production credit stems from rural commercial banks. In China, rural commercial banks are the primary source for micro—and—small—enterprise (MSE) banks. Thus, a “YES” response implies that the main funding providers are MSE banks, while a “NO” response implies that the main funding providers are large banks. Based on this, we obtain the empirical results presented in columns 1 and 2 of Table 9.

Table 9. Agricultural Digital Transformation and Agricultural Productive Credit Availability: Different bank sizes and farmland areas.

Variables	(1)	(2)	(3)	(4)
	loan_ag			
	small banks	Big banks	small farmers	Large farmers
agri_ict	67.603 (56.802)	147.255** (64.988)	33.890** (17.007)	50.821 (36.517)
Individual control variables	YES	YES	YES	YES
Family control variables	YES	YES	YES	YES
Constant	-141.928 (129.842)	-246.594* (136.528)	-48.170 (42.417)	-65.998 (160.763)
Observations	183	83	279	305
R-squared	0.177	0.202	0.103	0.071

As presented in columns 1 and 2 of Table 9, the empirical results suggest that, in comparison with small banks, the impact of agricultural digital transformation on agricultural production credit is positively significant at the 5% significance level only when the credit—supplying entity is a large bank. This implies that having large banks as the credit—supplying entity is more conducive to promoting agricultural digital transformation and facilitating farmers’ access to agricultural production credit. A possible reason is that, relative to small banks, large banks have a higher level of financial—technology development. Consequently, large banks are more likely to obtain the digital footprint generated by agricultural digital transformation at a lower cost, thereby facilitating farmers’ access to agricultural production credit.

4.5.2. Heterogeneity by Farmland Area

Different operating scales will also influence farmers’ capacity to obtain agricultural production credit. Consequently, this paper classifies the main users of funds into two categories according to whether the farmland area cultivated by farmers exceeds the sample median. If the farmland area cultivated by farmers is less than the sample median, they are regarded as small—scale farmers. If the farmland area cultivated by farmers is greater than the sample median, they are regarded as large—scale farmers. Based on this, we obtain the empirical results presented in columns 3 and 4 of Table 9.

The empirical results in columns 3 and 4 of Table 9 demonstrate that, in comparison with large—scale farmers, the impact of agricultural digital transformation on agricultural production credit is positively significant at the 5% significance level when the main demanders are small—scale farmers. This implies that agricultural digital transformation is more conducive to small—scale farmers in obtaining agricultural production credit. A possible reason is that large—scale farmers possess more complete financial systems, which facilitates banks and other financial institutions in evaluating their creditworthiness. Hence, agricultural digital transformation has a smaller impact on large—scale farmers’ access to agricultural production credit. Given that small—scale farmers lack hard information such as financial statements, agricultural digital transformation becomes an important basis for banks and other financial institutions to assess their creditworthiness.

4.5.3. Heterogeneity by Agricultural Digitalization Behaviors

In the foregoing analysis, this paper predominantly utilized the agricultural digital—transformation index as an explanatory variable. Nevertheless, different types of digital footprints (Berg et al., 2020) do not have precisely the same impact on credit assessment. In light of this, this paper will analyze whether there are significant differences in the impact of the use of information and communication technologies (ICT) on farmers’ access to agricultural production credit across various production and management stages, such as agricultural product sales, procurement of production materials, agricultural information facilities, online agricultural—technology services, and technical exchanges. The specific empirical results are presented in Table 10.

Table 10. Agricultural Digital Transformation and Agricultural Productive Credit Availability: Different Agricultural Digitalization Behaviors.

Variables	(1)	(2)	(3)	(4)	(5)
	Loan_ag	Loan_ag	Loan_ag	Loan_ag	Loan_ag
Ict_sale	22.356** (9.365)				
Ict_input		-12.544 (31.097)			
Ict_equipment			20.718** (9.524)		
Ict_assistance				5.741 (9.506)	

Ict_exchange					-5.375 (10.491)
Individual control variables	YES	YES	YES	YES	YES
Family control variables	YES	YES	YES	YES	YES
Constant	-61.218 (56.416)	-29.015 (65.013)	-57.249 (56.326)	-43.378 (56.155)	-36.284 (57.322)
Observations	559	559	559	559	559
R-squared	0.133	0.124	0.131	0.124	0.124

Significant at 10% (*), 5% (**), 1% (***) levels.

As presented in Table 10, the utilization of ICT technology in agricultural product sales and agricultural digital equipment management is more beneficial for farmers’ access to agricultural productive credit compared with the use of ICT technology in production material purchases, agricultural technical services, and technical exchanges. This finding might be ascribed to the fact that digital sales platforms for agricultural products offer financial institutions better insights into the professional capabilities of farmers’ agricultural operations, which helps in evaluating their repayment capacity. Moreover, the use of agricultural digital hardware or software enhances financial institutions’ ability to monitor farmers’ post—loan production and operational behaviors, thus reducing post—loan moral hazard. As a result, the digitization of agricultural product sales and the implementation of agricultural digital equipment are more effective in facilitating farmers’ access to agricultural productive credit compared to other areas of production and operation.

5. Conclusion and Discussion

5.1. Conclusion and Discussion

In particular, we conducted empirical tests using a large sample of 585 family farms from seven prefecture—level cities in Jiangsu Province, China, in 2023. Our research reveals that the adoption of ICT technologies in agricultural production significantly enhances farmers’ access to agricultural productive credit. This conclusion remains robust when considering sample—selection bias and endogeneity issues, suggesting a causal link between the digital transformation of agriculture and improved agricultural productive credit conditions for farmers.

Regarding transmission mechanisms, agricultural digital transformation can facilitate farmers’ access to agricultural production credit by reducing credit—transaction costs. At the same time, agricultural digital transformation can also have a positive impact on farmers’ access to agricultural production credit by improving the efficiency of their agricultural resource allocation.

In terms of heterogeneity analysis, compared with small banks, agricultural digital transformation is more conducive to farmers obtaining agricultural production credit from large banks. Compared with large—scale farmers, agricultural digital transformation is more conducive to small—scale farmers obtaining agricultural production credit. Finally, compared with other production and operation links, the application of ICT in the areas of agricultural product sales and agricultural digital equipment management is more conducive to farmers obtaining agricultural production credit.

In summary, this paper is the first to empirically analyze the relationship between the adoption of ICT technology in agricultural production and farmers’ access to agricultural productive credit. Our study shows that the integration of ICT technology can assist farmers in securing better credit conditions by providing financial intermediaries with more detailed, transparent, and easily verifiable information. Moreover, the use of ICT in agricultural production can increase agricultural output and strengthen repayment capabilities.

5.2. Limitations and Future Prospects

One limitation of this study is its exclusive focus on samples from China. Consequently, further research is required to ascertain whether these findings are applicable to other developing countries.

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References

- Agarwal S, Hauswald R. Distance and private information in lending[J]. *The Review of Financial Studies*, 2010, 23(7): 2757-2788.
- Agbodji A E, Johnson A A. Agricultural credit and its impact on the productivity of certain cereals in Togo[J]. *Emerging Markets Finance and Trade*, 2021, 57(12): 3320-3336.
- Agyekumhene C, de Vries J R, van Paassen A, et al. Digital platforms for smallholder credit access: The mediation of trust for cooperation in maize value chain financing[J]. *NJAS-Wageningen Journal of Life Sciences*, 2018, 86: 77-88.
- Allen R C. Agricultural productivity and rural incomes in England and the Yangtze Delta, c. 1620–c. 1820 1[J]. *The Economic History Review*, 2009, 62(3): 525-550.
- Altonji J G, Elder T E, Taber C R. Selection on observed and unobserved variables: Assessing the effectiveness of Catholic schools[J]. *Journal of Political Economy*, 2005, 113(1): 151-184.
- Akpan S B, Patrick I V, Udoka S J, et al. Determinants of credit access and demand among poultry farmers in Akwa Ibom State, Nigeria[J]. *American Journal of Experimental Agriculture*, 2013, 3(2): 293.
- Asongu S, Le Roux S, Nwachukwu J, et al. Reducing information asymmetry with ICT: A critical review of loan price and quantity effects in Africa[J]. *International Journal of Managerial Finance*, 2019, 15(2): 130-163.
- Berg T, Burg V, Gombović A, et al. On the rise of fintechs: Credit scoring using digital footprints[J]. *The Review of Financial Studies*, 2020, 33(7): 2845-2897.
- Chen Z, Zhang Y, Zhou L. Has financial access improved agricultural technical efficiency?—evidence from two family farm demonstration zones in China[J]. *China Agricultural Economic Review*, 2022, 14(1): 142-164.
- Cheng W, Zhou N, Zhang L. How does land titling affect credit demand, supply, access, and rationing: Evidence from China[J]. *Canadian Journal of Agricultural Economics*, 2021, 69(3): 383-414.
- Coase R H. The problem of social cost[J]. *The journal of Law and Economics*, 2013, 56(4): 837-877.
- Drewry J L, Shutske J M, Trechter D, et al. Assessment of digital technology adoption and access barriers among crop, dairy and livestock producers in Wisconsin[J]. *Computers and Electronics in Agriculture*, 2019, 165: 104960.
- Fecke W, Feil J H, Musshoff O. Determinants of loan demand in agriculture: empirical evidence from Germany[J]. *Agricultural finance review*, 2016, 76(4): 462-476.
- Hou J, Huo X, Yin R. Does computer usage change farmers' production and consumption? Evidence from China[J]. *China Agricultural Economic Review*, 2019, 11(2): 387-410.
- Kannan E. Relationship between agricultural credit policy, credit disbursements and crop productivity: A study in Karnataka[J]. *Indian Journal of Agricultural Economics*, 2011, 66(3).
- Kehinde A, Bamire A S. Determinants of Demand and Supply of Microcredit Among Fish Farmers in Osun State[J]. *Journal of Agribusiness and Rural Development*, 2023, 67(1): 5-18-5-18.
- Klerkx L, Jakku E, Labarthe P. A review of social science on digital agriculture, smart farming and agriculture 4.0: New contributions and a future research agenda[J]. *NJAS-Wageningen journal of life sciences*, 2019, 90: 100315.
- Kumar S M. Does access to formal agricultural credit depend on caste?[J]. *World Development*, 2013, 43: 315-328.
- Kvartiuk V, Petrick M. Liberal land reform in Kazakhstan? The effect on land rental and credit markets[J]. *World Development*, 2021, 138: 105285.

- Latief R, Zhang L. Nexus between government agricultural expenditures and agricultural credit: The role of sustainable agricultural growth and sustainable agricultural income[J]. *Sustainable Development*, 2023.
- Ma W, Qiu H, Rahut D B. Rural development in the digital age: Does information and communication technology adoption contribute to credit access and income growth in rural China?[J]. *Review of Development Economics*, 2023, 27(3): 1421-1444.
- Mishra K, Gallenstein R A, Miranda M J, et al. Insured loans and credit access: Evidence from a randomized field experiment in northern Ghana[J]. *American Journal of Agricultural Economics*, 2021, 103(3): 923-943.
- Mittal S. Modern ICT for agricultural development and risk management in smallholder agriculture in India[M]. CIMMYT, 2012.
- Moreira-Dantas I R, Martínez-Zarzoso I, Henning C, et al. Rural credit acquisition for family farming in Brazil: Evidence from the Legal Amazon[J]. *Journal of Rural Studies*, 2023, 101: 103041.
- Nakano Y, Magezi E F. The impact of microcredit on agricultural technology adoption and productivity: Evidence from randomized control trial in Tanzania[J]. *World Development*, 2020, 133: 104997.
- Oyinbo O, Chamberlin J, Abdoulaye T, et al. Digital extension, price risk, and farm performance: experimental evidence from Nigeria[J]. *American Journal of Agricultural Economics*, 2022, 104(2): 831-852.
- Ozdogan B, Gacar A, Aktas H. Digital agriculture practices in the context of agriculture 4.0[J]. *Journal of Economics Finance and Accounting*, 2017, 4(2): 186-193.
- Pingali P, Khwaja Y, Meijer M. Commercializing small farms: Reducing transaction cost[J]. 2005.
- Riley E. Mobile money and risk sharing against village shocks[J]. *Journal of Development Economics*, 2018, 135: 43-58.
- Sheng J, Lu Q. The influence of information communication technology on farmers' sales channels in environmentally affected areas of China[J]. *Environmental Science and Pollution Research*, 2020, 27(34): 42513-42529.
- Smidt H J, Jokonya O. Factors affecting digital technology adoption by small-scale farmers in agriculture value chains (AVCs) in South Africa[J]. *Information Technology for Development*, 2022, 28(3): 558-584.
- Suri T, Bharadwaj P, Jack W. Fintech and household resilience to shocks: Evidence from digital loans in Kenya[J]. *Journal of Development Economics*, 2021, 153: 102697.
- Tang K. Industrial-organization-transformation-oriented agricultural modernization with Chinese characteristics: from the perspective of industrial and agricultural interaction[J]. *International Journal of Business and Management*, 2011, 6(5): 211.
- Xie L, Luo B, Zhong W. How are smallholder farmers involved in digital agriculture in developing countries: A case study from China[J]. *Land*, 2021, 10(3): 245.
- Zhang Z, Tian Y, Chen Y H. Can agricultural credit subsidies affect county-level carbon intensity in China?[J]. *Sustainable Production and Consumption*, 2023, 38: 80-89.

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