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Rural development in the digital age: Does information and communication technology adoption contribute to credit access and income growth in rural China?

Wanglin Ma[1] | Huanguang Qiu[2] | Dil Bahadur Rahut[3]

[1]Department of Global Value Chains and Trade, Faculty of Agribusiness and Commerce, Lincoln University, Christchurch, New Zealand

[2]School of Agricultural Economics and Rural Development, Renmin University of China, Beijing, China

[3]Asian Development Bank Institute, Tokyo, Japan

Correspondence
Huanguang Qiu, School of Agricultural Economics and Rural Development, Renmin University of China, Beijing, China.
Email: hgqiu@ruc.edu.cn

Abstract

Information and communication technology (ICT) plays an important role in rural livelihoods and household well-being. Therefore, this study examines the impact of ICT adoption on farmers' decisions to access credit and the joint effects of ICT adoption and access to credit on household income using 2016 China Labour-force Dynamics Survey data. Both recursive bivariate probit model and a selectivity-corrected ordinary least square regression model are employed for the analysis. The results show that ICT adoption increases the probability of access to credit by 12.8% in rural China and empowers rural women and farm households in relatively less-developed regions to access credit. ICT adoption and access to credit affect household income differently. ICT adoption significantly increases household income, while access to credit significantly reduces it, primarily because farmers do not use the acquired credit to invest in income-generating farm and off-farm business activities. ICT adoption has the largest positive impact on household income at the highest 90th quantile. Our findings suggest that improving rural ICT infrastructure to enhance farmers' ICT adoption and developing

ICT-based financial products to enable households to access sufficient funds can improve rural household welfare.

1 | INTRODUCTION

Access to credit plays an important role in improving agricultural production and alleviating poverty in rural areas of developing and emerging countries. Credit eases liquidity and facilitates farm households to purchase productivity-enhancing inputs (e.g., improved seeds, fertilizers, and pesticides) (Kehinde & Ogundeji, 2022; Osabohien, Mordi, & Ogundipe, 2022), invest in the farm and off-farm businesses (Ejemeyovwi, Osabuohien, & Bowale, 2021), smoothen household consumption (Kumar, Mishra, Sonkar, & Saroj, 2020; Li, Lin, & Gan, 2016), and cope with short-term nondelinquent expenditures, such as sickness prevention and treatment (Felkner, Lee, Shaikh, Kolata, & Binford, 2022) and children's education (Kandulu, Wheeler, Zuo, & Sim, 2019). In addition, access to credit can empower rural women by enabling them to purchase productive assets. For example, credit enables the purchase of women-oriented durable goods and services such as sewing machines and washers and farm machinery and relevant services to maintain farm production when men migrate for better salary opportunities (Basumatary, Chhetri, & Rajesh, 2022; Datta & Sahu, 2021; Paudel, Gartaula, Rahut, & Craufurd, 2020).

Despite the importance of access to credit, rural households are usually unable to acquire credit easily or get the credit amount they need due to various constraints, including the lack of credit market and services, arrangements of regional financial institutions, lack of collateral and information asymmetry (Akudugu, Egyir, & Mensah-Bonsu, 2009; Benami & Carter, 2021; Kehinde & Ogundeji, 2022; Kofarmata & Danlami, 2019; Li, Ma, Mishra, & Gao, 2020). In particular, information asymmetry has been identified as a major obstacle. In the investigations on Ghana and Nigeria, Akudugu et al. (2009) and Kofarmata and Danlami (2019) found that asymmetric information increases the risks of borrowers' moral hazard and adverse selection, which restricts rural households from participating in the credit markets and obtaining the required loan amount. Therefore, it is important to reduce information asymmetry between borrowers and lenders to improve farm households' ability to access credit.

Adopting information and communication technologies (ICTs) such as computers and mobile phones can reduce information asymmetry in the digital age. ICT-based analytical tools can help both borrowers and lenders better understand the market risks and improve their efficiency and effectiveness in dealing with potential information asymmetry and moral hazards (Asongu, le Roux, Nwachukwu, & Pyke, 2019). Several studies found that ICT adoption enhances farm economic performance (Ogutu, Okello, & Otieno, 2014), increases rural households' income (Leng, Ma, Tang, & Zhu, 2020; Ma, Grafton, & Renwick, 2020), and facilitates

rural development (Niebel, 2018; Spielman, Lecoutere, Makhija, & Van Campenhout, 2021). For example, Ogutu et al. (2014) showed that ICT-based market information services increase the use of purchased seeds and fertilizers and labor productivity in Kenya. Ma et al. (2020) found that in rural China ICT adoption in terms of smartphone use increases farm income, off-farm income, and overall household income. ICT also enables mobile money usage (i.e., making basic financial transactions via smartphones), which reduces borrowing costs (Kim, 2022; Lashitew, van Tulder, & Liasse, 2019; Munyegera & Matsumoto, 2018). Very few studies have explored the relationship between ICT adoption and rural households' financial accessibility. A notable exception is a study by Asongu et al. (2019), who analyzed panel data of 162 banks from 42 African countries and showed that ICT adoption decreases loan prices and increases loan quantity in their analysis. Moreover, farmers may simultaneously make decisions on ICT adoption and credit access to maximize their expected household welfare, but no previous studies have explored the joint effects of ICT adoption and access to credit.

The primary objective of this study is, therefore, to investigate the relationship between ICT adoption and access to credit, as well as their joint effects on household income, using the 2016 China Labour-force Dynamics Survey (CLDS) data collected by the Centre for Social Science Survey at Sun Yat-sen University in Guangzhou, China. Although the CLDS collected data from both rural and urban households, this study focuses only on rural households because they are more likely to be credit-constrained compared to their urban counterparts and rural financial markets are not mature (Kofarmata & Danlami, 2019; Yuan & Xu, 2015).

This study contributes to the literature in several aspects. First, we analyze the impact of ICT adoption on access to credit. We use a recursive bivariate probit (RBP) model to address the selection bias issue that usually occurs when farmers self-select themselves as ICT adopters or non-adopters. Previous studies have employed a propensity score matching (PSM) approach to mitigate selection bias associated with ICT adoption (Minah, 2022; Shimada & Sonobe, 2021). However, the PSM approach is unable to mitigate selection bias issues arising from unobserved factors. Second, we explore whether there exist heterogeneous effects of ICT adoption on access to credit between male- and female-headed households and among geographical locations. Extant studies have confirmed that a gender divide exists in ICT adoption (Leng et al., 2020; Nikam, Ashok, & Pal, 2022; Silver & Cornibert, 2019). Thus, the impact of ICT adoption on access to credit might be heterogeneous between male- and female-headed households. Moreover, the institutional arrangements, socioeconomic conditions, ICT infrastructure conditions, and resource endowments differ among different geographical locations in China, so it is worth investigating whether there are heterogeneous regional effects of ICT adoption.

Third, we explore the joint effects of ICT adoption and access to credit on household income. Previous studies have either examined the effects of ICT adoption (Colombo, Croce, & Grilli, 2013; Khan, Ray, Zhang, Osabuohien, & Ihtisham, 2022; Leng et al., 2020; Ma & Zheng, 2022) or analyzed the effects of access to credit (Al-shami, Razali, & Rashid, 2018; Ankrah Twumasi, Jiang, Fosu, Addai, & Essel, 2022; Kehinde & Ogundeji, 2022; Li et al., 2020; Osabohien et al., 2022). However, given that farmers may make joint decisions in their efforts to adopt ICTs and acquire credit, modeling the separate effects of ICT adoption and access to credit on household income would generate biased and inconsistent estimates. Fourth, we further estimate the impact of ICT adoption and access to credit on farm income and business income. This estimation enables us to intuitively understand whether farmers have used the ICTs and acquired credit to invest in income-generating farm and off-farm activities. Finally, we estimate an unconditional quantile regression (UQR) model to check whether the impacts
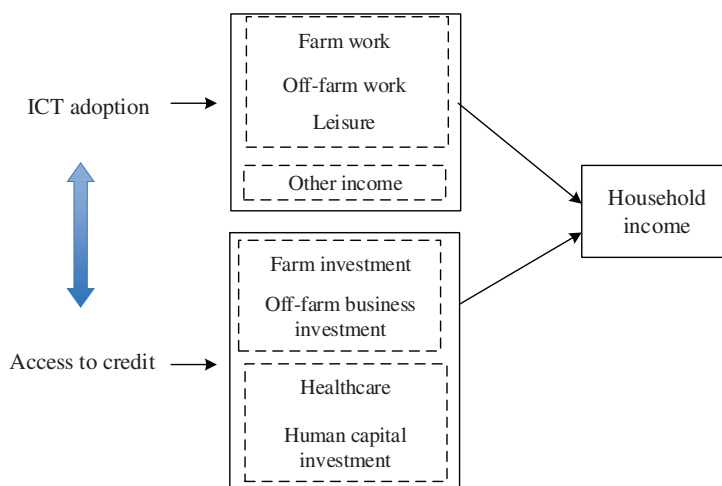
of ICT adoption and access to credit on household income are homogenous or heterogeneous. From a policy perspective, policymakers are usually interested in understanding how ICT interventions and credit market development in rural areas affect the unconditional distributions of an outcome such as household income.

This paper is structured as follows: Section 2 introduces the conceptual framework. Section 3 presents econometric models, and Section 4 presents data and descriptive statistics. Section 5 offers and discusses the empirical results. The final section concludes with policy implications and research limitations.

2 | CONCEPTUAL FRAMEWORK

Figure 1 illustrates the potential relationship between ICT adoption, access to credit, and household income. The first path shows that farmers' decisions to adopt ICT and access to credit can affect each other. On the one hand, ICT adoption reduces information asymmetry associated with credit markets and stimulates mobile money usage (Asongu et al., 2019; Ejemeyovwi et al., 2021; Kim, 2022), and thus, farmers adopting ICTs may be more likely to obtain credit. Munyegera and Matsumoto (2018) showed that mobile money leverages rural households' financial access constraints in Uganda and stimulates remittance and borrowing transactions between farm households. On the other hand, access to credit may also affect ICT adoption. Credit obtained from informal sources (e.g., friends and relatives) and formal sources (e.g., banks and credit cooperatives) enables farmers to relax capital constraints. For example, farmers may use the obtained credit to purchase ICT devices such as smartphones and computers.

The second path shows that ICT adoption can affect farm work, off-farm work, leisure, and other income, which ultimately affects household income. The farm household model suggests that rural farmers allocate their fixed time to farm work, off-farm work, and leisure (Fernandez-Cornejo et al., 2007). Previous studies have shown that ICT adoption improves farm

FIGURE 1 Potential relationship between information and communication technology (ICT) adoption, access to credit, and household income [Colour figure can be viewed at wileyonlinelibrary.com]

investments and productivity (Agbodji & Johnson, 2021; Kaila & Tarp, 2019; Ma & Zheng, 2022), off-farm work participation (Hartje & Hübler, 2017; Rajkhowa & Qaim, 2022), and farmers' leisure time (e.g., chatting, playing games, buying lotteries online, gambling, watching videos, and browsing webpages on smartphones and computers) and quality of life (Kirova & Vo Thanh, 2019; Mnisi & Alhassan, 2021). Thus, ICT adoption affects farmers' farm and off-farm income and overall household income. For example, more time allocated to ICT-based leisure would result in less time allocated to ICT-based farm and off-farm activities, which indicates a negative effect of ICT adoption on household income, and vice versa. Besides, ICT adoption can affect household income by providing opportunities for other income sources, such as remittance (Kirui, Okello, Nyikal, & Njiraini, 2013; Munyegera & Matsumoto, 2016).

The third path shows that access to credit can also affect household income by directly influencing households' economic activities. Rural households may acquire credit to support farm investment and off-farm business. Petrick (2004) found that access to subsidized credit is positively associated with farmers' farm investment behavior in Poland. Abate, Rashid, Borzaga, and Getnet (2016) showed that improving access to credit increases smallholder farmers' adoption of agricultural technologies, including fertilizers and improved seed varieties in Ethiopia. In Bangladesh, access to credit positively influences the adoption of farm machinery (Mottaleb, Rahut, Ali, Gérard, & Erenstein, 2017), which ultimately affects farm productivity and household income. Banerjee and Jackson (2017) revealed that the microfinance program implemented in Bangladesh provides the poor with new opportunities for entrepreneurship, which helps generate income and reduce poverty. Therefore, access to credit may increase household income. However, farmers may seek credit for health care and children's education (Chein & Pinto, 2018; Kandulu et al., 2019; Sun & Yannelis, 2016) rather than investing in income-generating activities, which indicates that access to credit may have a negative or no impact on household income. For example, suppose credit users do not use the acquired credit for income-generating activities but use it for other household activities such as children's education and medical treatment, while nonusers of credit invest in income-generating activities using their funds. In that case, access to credit might negatively impact household income.

In this study, we quantitatively examine to what extent and how ICT adoption affects access to credit and the joint effects of ICT adoption and access to credit on household income, using rigorous econometric approaches. The findings of this study would inform policymakers regarding what efforts they should make to improve farmers' ICT adoption and financial access status, aimed at promoting rural development and economic growth.

3 | ECONOMETRIC MODELS

3.1 | Modeling the impact of ICT adoption on access to credit

Households decide themselves (self-selection), whether to adopt the ICTs, depending on their welfare and other socioeconomic and technological factors, which leads to the potential endogeneity issue of the ICT adoption variable in an econometric estimation. When analyzing the impact of a binary endogenous treatment variable (i.e., ICT adoption) on a binary outcome variable (i.e., access to credit), previous studies have suggested different approaches, such as the PSM method (Minah, 2022; Shimada & Sonobe, 2021), endogenous switching probit (ESP) model (Lokshin & Sajaia, 2011; Nkegbe et al., 2022), and RBP model (Addai, Temoso, & Ng'ombe, 2022; Li, Cheng, & Shi, 2021). Among them, the PSM method fails to correct for

endogeneity issues originating from unobserved factors (e.g., an individual's innate ability and motivation), while the ESP model cannot estimate a direct effect of ICT adoption on access to credit. In comparison, the RBP model addresses the endogeneity issue from both observed and unobserved factors, and it can estimate a direct marginal effect of ICT adoption on access to credit. Therefore, our estimation uses the RBP model.

The RBP model estimates two equations (Addai et al., 2022; Li et al., 2021). One describes the probability of ICT adoption based on Equation 1, and another explains the impact of ICT adoption on households' credit access based on Equation 2:

$$I_i^* = \eta_i X_i + \xi_i IV_i + \tau_i, \ I_i = \begin{cases} 1, \text{if } I_i^* > 0 \\ 0, \text{otherwise} \end{cases} \tag{1}$$

$$C_i^* = \alpha_i I_i + \beta_i X_i + \varepsilon_i, C_i = \begin{cases} 1, \text{if } C_i^* > 0 \\ 0, \text{otherwise} \end{cases} \tag{2}$$

where I_i^* is a latent variable representing the probability that a household i adopts ICTs, which is determined by the observed binary variable I_i ($I_i = 1$ for ICT adopters and $I_i = 0$ for non-adopters); C_i^* refers to a latent variable that represents the propensity of credit access, which is determined by the observed binary variable C_i ($C_i = 1$ for credit users and $C_i = 0$ for non-users); X_i is a vector of exogenous variables; IV_i refers to an instrumental variable (IV), which is used for RBP model identification; η_i, ξ_i, α_i, and β_i are parameters to be estimated; τ_i and ε_i are error terms.

Because we could not identify a valid instrumental variable (IV) from the available variables in the CLDS data set, we follow previous studies (Zheng, Ma, & Zhou, 2021; Zhu, Ma, Sousa-Poza, & Leng, 2020) and use a synthesized IV. The synthesized IV represents the average number of other ICT adopters (i.e., except for the sampled household) within the same county. We expect that the synthesized IV affects a household's ICT adoption decision, but we do not expect it to affect access to credit directly. Statistically, we conduct a Pearson correlation analysis to test the validity and effectiveness of the IV. The results (see Table A1) show that the IV is significantly correlated with the ICT adoption variable, but it is not significantly correlated with the access to credit variable, confirming the appropriateness of the IV.

The full information maximum likelihood estimator simultaneously estimates Equations 1 and 2. This procedure generates a correlation coefficient between the two error terms in Equations 1 and 2, that is, $\rho_{\tau\varepsilon} = corr(\tau_i, \varepsilon_i)$. If $\rho_{\tau\varepsilon}$ is statistically significant, it would suggest the presence of selection bias arising from the unobserved factors (Addai et al., 2022), and estimating the impact of ICT adoption on access to credit using other approaches such as PSM or simple probit model may generate biased estimates.

3.2 | Modeling the joint effects of ICT adoption and access to credit on household income

To examine the joint effects, we assume that household income is a function of the ICT adoption, access to credit, and a vector of explanatory variables. The regression equation for household income can be rewritten as follows:

$$Y_i = \gamma_i I_i + \delta_i C_i + \varphi_i X_i + \varpi_i \tag{3}$$

where Y_i refers to household income, which is measured at 1,000 Yuan/capita; I_i, C_i, and X_i are variables defined earlier; γ_i, δ_i, and φ_i are parameters to be estimated; ϖ_i is an error term. γ_i and δ_i are parameters capturing the impacts of ICT adoption and access to credit on household income, respectively. Equation 3 can be estimated using an ordinary least square (OLS) regression model.

As discussed earlier, the ICT adoption variable (I_i) is endogenous in Equation 3, because farmers select themselves as ICT adopters or non-adopters. Access to credit variable (C_i) is also potentially endogenous in Equation 3 due to the similar self-selection issue of becoming credit users or nonusers. The endogeneity issue of access to credit variables has been discussed in previous studies (Kumar et al., 2020; Li et al., 2020). Failing to address the endogeneity issues associated with ICT adoption and access to credit variables would produce biased estimates regarding their joint effects on household income.

Following previous studies (Ma, Renwick, & Grafton, 2018; Wooldridge, 2015), we employ a two-stage selectivity-corrected OLS model to estimate the unbiased impacts of ICT adoption and access to credit on household income. In the first stage, the two equations of ICT adoption and access to credit are jointly estimated using a seemingly unrelated bivariate probit (SUBP) model. The SUBP model simultaneously estimates an ICT adoption equation and access to credit equation. Unlike the RBP model estimation, the ICT adoption variable is removed from Equation 2 in the SUBP model estimation to avoid a reverse causality relationship between ICT adoption and access to credit. The results estimated by the SUBP model are used to generate predicted variables for the endogenous factors. In the second stage, the predicted ICT adoption variable and predicted access to credit variable, which controls for the endogeneity issues, are used to replace the original variables in Equation 3. Therefore, the following selectivity-corrected OLS model can be estimated:

$$Y_i = \zeta_i I'_i + \lambda_i C'_i + \psi_i X_i + \omega_i \tag{4}$$

where Y_i and X_i are variables defined previously; I'_i and C'_i are predicted ICT adoption variable and predicted access to credit variable, respectively; ζ_i, λ_i, and ψ_i are parameters to be estimated; ω_i is an error term.

4 | DATA AND DESCRIPTIVE STATISTICS

4.1 | Data

Data used in this paper were obtained from the CLDS, which was conducted in 2016 by the Centre for Social Science Survey at Sun Yat-sen University in Guangzhou, China. The data were collected from western, central, and eastern regions, covering 29 provinces of mainland China (excluding Tibet Autonomous Region and Hainan). The questionnaire includes detailed information on individual and household-level characteristics, household daily life activities, the use of ICTs, housing conditions, households' financial performance, rural labor migration, and agricultural production and marketing. The 2016 CLDS survey comprises 14,200 samples, including 8,248 rural households and 5,952 urban households. The data cleaning took three steps. First,

we excluded the samples of urban households. Second, we removed rural samples with missing values in household income, farm income, and business income. Third, we further dropped samples with missing information on the control variables (e.g., age, education, car ownership, and pension). Finally, we obtained a total of 7,771 rural household samples for empirical analysis.

ICT adoption is measured as a dichotomous variable, which equals one if a farm household adopts the Internet-connected ICTs such as computers and mobile phones in 2015, and zero otherwise. Access to credit is also measured as a dichotomous variable, which equals one if a farm household has access to credit from any formal credit sources (e.g., banks and credit unions) and informal credit sources (e.g., friends and relatives). Household income refers to total household income generated from farm work, business investment, salaries, property, and remittance, which is measured at 1,000 Yuan/capita. Farm income refers to the income generated from agriculture, forestry, animal husbandry, and fishery, while business income refers to income from an off-farm business such as grocery stores and family workshops.

4.2 | Descriptive statistics

Table 1 presents the definitions and descriptive statistics of the variables used in the analysis. It shows that 32.5% of households adopt the ICTs, and 44.9% have access to credit. The average household income is 10,171 Yuan/capita. The mean age of the household heads is 52 years, and more than half (57.1%) are male. Only 15.2% of the rural households own cars, and around 5.9% are specialized in agricultural production.[1]

Table 2 presents the mean differences of the variables between ICT adopters and non-adopters. Compared with the non-adopters, ICT adopters are 14.8% more likely to access credit and are also more likely to obtain a higher household income. ICT adopters are younger and more likely to own a car and an indoor toilet than non-adopters. ICT adopters are also more likely to specialize in agricultural production than their non-adopter counterparts. More generally, the mean differences indicate that the ICT adopters and non-adopters are systematically different, primarily because farmers select themselves as ICT adopters or non-adopters. Therefore, the empirical analysis cannot ignore the endogeneity issue associated with the ICT adoption variable.

Figure 2 demonstrates the means of access to credit variables by gender. Male ICT adopters are more likely to acquire credit than female ICT adopters. While among the ICT non-adopters, the mean of access to credit for the female is higher than that for the male. Figure 3 presents the means of access to credit variables by geographical locations. ICT adopters in the western region have the highest probability of acquiring credit, while the non-adopters in the eastern region have the lowest likelihood of obtaining credit. The information presented in Figures 2 and 3 suggests that ICT adoption may generally affect access to credit heterogeneously between male- and female-headed households and among geographical locations. Thus, we also quantitatively estimate the heterogeneous effects of ICT adoption on access to credit in the empirical section.

5 | EMPIRICAL RESULTS AND DISCUSSION

5.1 | Results of the RBP model estimation

The coefficient estimates of the RBP model are presented in Table A2 for reference. As discussed earlier, the RBP model jointly estimates Equations 1 and 2. The results in the lower part

TABLE 1 Variable definitions and descriptive statistics

Variables	Definitions	Mean (SD)
Dependent variables		
ICT adoption	1 if household adopts the ICTs such as computer and/or smartphones, 0 otherwise	0.325 (0.468)
Access to credit	1 if household has access to credit from various sources (e.g., banks, credit unions, friends, and/or relatives), 0 otherwise	0.449 (0.497)
Household income	Annual household income (1,000 Yuan/capita)[a]	10.171 (13.387)
Farm income	Annual income from agriculture, forestry, animal husbandry, and fishery (1,000 Yuan/capita)	2.579 (6.632)
Business income	Business investment income (1,000 Yuan/capita)	1.448 (7.435)
Independent variables		
Age	Age of household head (HH) in years	51.671 (14.662)
Gender	1 if HH is male, 0 otherwise	0.571 (0.495)
Illiteracy	1 if HH's education level is illiteracy, 0 otherwise	0.191 (0.393)
Primary school	1 if HH's education level is a primary school, 0 otherwise	0.360 (0.480)
Middle-level school	1 if HH's education level is between primary school and college (i.e., middle school, high school, vocational high school, technical school, or technical secondary school), 0 otherwise	0.416 (0.493)
College and above	1 if HH's education level is college and above, 0 otherwise	0.033 (0.178)
Farm labor	Number of farm labor	1.036 (1.1)
Car ownership	1 if household owns a car, 0 otherwise	0.152 (0.359)
Indoor toilet	1 if household owns an indoor toilet, 0 otherwise	0.458 (0.498)
Pension	1 if HH receives a retirement pension, 0 otherwise	0.091 (0.288)
Soil quality	1 if soil quality is good, 0 otherwise	0.553 (0.497)
Specialization	1 if household specialized in farming, 0 otherwise	0.059 (0.235)
West	1 if household residents in western China, 0 otherwise	0.310 (0.463)
Central	1 if household residents in Central China, 0 otherwise	0.269 (0.444)
East	1 if household residents in eastern China, 0 otherwise	0.421 (0.494)
IV	The average number of other ICT adopters within the same county	0.449 (0.223)
Gift money	Annual spending on gift money (100 Yuan)	6.147 (65.596)

Abbreviations: ICT, information and communication technology; IV, instrumental variable.
[a]Yuan is the Chinese currency.

of Table A2 show that the estimated correlation coefficient $\rho_{\tau\varepsilon}$ is statistically significant and negative, suggesting the presence of negative selection bias originating from unobserved factors (Addai et al., 2022; Li et al., 2021). The negative selection bias implies that farmers having lower probabilities of adopting ICTs have higher probabilities of accessing credit. These findings suggest that failing to account for the selection bias issues would underestimate the impact of ICT

TABLE 2 Mean differences in the selected variables between ICT adopters and non-adopters

Variables	ICT adopters (N = 3,487)	Non-adopters (N = 4,284)	Mean-differences	t-Value
Access to credit	0.349 (0.477)	0.304 (0.460)	0.045***	4.259
Household income	13.693 (15.691)	7.303 (10.314)	6.390***	21.545
Age	45.740 (13.739)	56.498 (13.581)	−10.758***	−34.551
Gender	0.534 (0.499)	0.600 (0.490)	−0.066***	−5.868
Illiteracy	0.109 (0.312)	0.256 (0.437)	−0.147***	−16.713
Primary school	0.293 (0.455)	0.416 (0.493)	−0.123***	−11.343
Middle-level school	0.537 (0.499)	0.318 (0.466)	0.219***	19.940
College and above	0.061 (0.240)	0.010 (0.099)	0.052***	12.798
Farm labor	1.034 (1.199)	1.038 (1.012)	−0.004	−0.156
Car ownership	0.261 (0.439)	0.063 (0.244)	0.198***	25.092
Indoor toilet	0.565 (0.496)	0.370 (0.483)	0.195***	17.522
Pension	0.085 (0.279)	0.096 (0.295)	−0.011	−1.640
Soil quality	0.481 (0.500)	0.610 (0.488)	−0.129***	−11.461
Specialization	0.069 (0.254)	0.050 (0.218)	0.019***	3.631
West	0.248 (0.432)	0.361 (0.480)	−0.113***	−10.799
Central	0.218 (0.413)	0.311 (0.463)	−0.093***	−9.270
East	0.535 (0.499)	0.328 (0.470)	0.206***	18.734
IV	0.550 (0.211)	0.366 (0.197)	0.184***	39.597
Gift money	6.980 (1.210)	5.470 (0.920)	1.512	1.011

Note: Standard deviation in parentheses.
Abbreviations: ICT, information and communication technology; IV, instrumental variable.
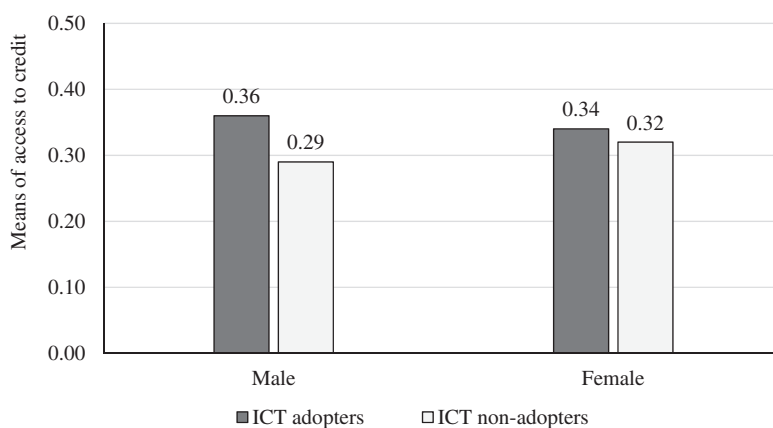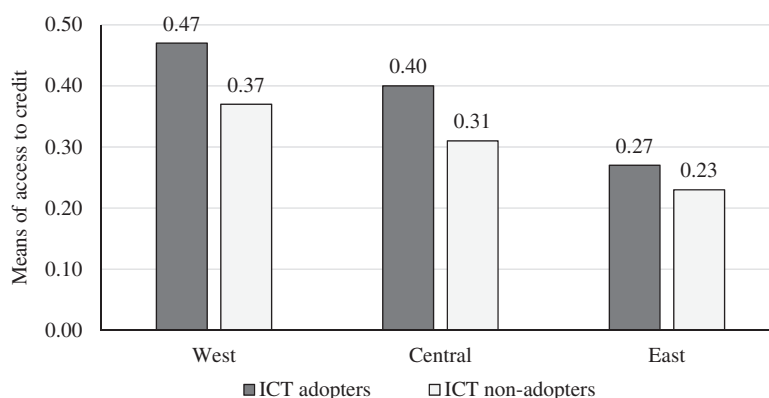***$p < 0.01$.

FIGURE 2 Means of access to credit by information and communication technology (ICT) adoption and gender

adoption on access to credit. The Wald test of $\rho_{\tau\varepsilon} = 0$ is also statistically significant, suggesting that we can reject the null hypothesis that there is no correlation between the selection and

FIGURE 3 Means of access to credit by information and communication technology (ICT) adoption and geographical locations

TABLE 3 Marginal effects of ICT adoption on access to credit

	RBP model		Probit model
Variables	**ICT adoption**	**Access to credit**	**Access to credit**
ICT adoption		0.128 (0.033)***	0.033 (0.012)***
Age	−0.004 (0.002)*	0.009 (0.002)***	0.008 (0.002)***
Age squared	−0.000 (0.000)*	−0.000 (0.000)***	−0.000 (0.000)***
Gender	−0.053 (0.010)***	0.005 (0.011)	−0.001 (0.011)
Primary school	0.040 (0.014)***	−0.016 (0.015)	−0.011 (0.015)
Middle-level school	0.123 (0.014)***	−0.050 (0.017)***	−0.035 (0.016)**
College and above	0.186 (0.036)***	−0.106 (0.035)***	−0.088 (0.035)**
Farm labor	0.018 (0.005)***	0.022 (0.005)***	0.023 (0.005)***
Car ownership	0.210 (0.014)***	−0.044 (0.017)***	−0.020 (0.015)
Indoor toilet	0.092 (0.010)***	−0.001 (0.012)	0.011 (0.011)
Pension	−0.060 (0.018)***	−0.067 (0.020)***	−0.072 (0.020)***
Soil quality	−0.036 (0.009)***	−0.008 (0.011)	−0.014 (0.011)
Specialization	0.057 (0.020)***	0.044 (0.022)**	0.051 (0.022)**
Central	0.022 (0.012)*	−0.046 (0.014)***	−0.044 (0.014)***
East	0.028 (0.012)**	−0.153 (0.013)***	−0.142 (0.013)***
IV	0.601 (0.022)***		
Observations	7,771		7,771

Note: Standard errors in parentheses. The reference region is west. The reference education level is illiteracy.
Abbreviations: ICT, information and communication technology; IV, instrumental variable.
*$p < 0.1$. **$p < 0.05$. ***$p < 0.01$.

outcome equations. The finding indicates that it is more appropriate to estimate the ICT adoption equation and access to credit equation jointly rather than separately.

Since the explanation of coefficient estimates from the RBP model (Table A2) is not straightforward, we calculate the marginal effects of the explanatory variables and present the results

in Table 3 to improve our understanding of the determinants of ICT adoption and access to credit.

5.1.1 | Determinants of ICT adoption

The results for the factor influencing ICT adoption are presented in the second column of Table 3. The marginal effect of the gender variable is negative and statistically significant, suggesting that compared to male household heads, their female counterparts are 5.3% more likely to adopt the ICTs. Our result is consistent with the finding of Martínez-Domínguez and Mora-Rivera (2020), who found that women are more likely to adopt the ICTs with Internet access for information searches, communication, and social networks in rural Mexico. The significant marginal effects of the education variables suggest that compared to illiterate people, those with primary school, middle-level school, and college education are 4%, 12.3%, and 18.6% more likely to adopt ICTs. The positive correlation between education and ICT adoption is also found in the literature (Ma et al., 2020; Mishra, Williams, & Detre, 2009). For example, Mishra et al. (2009) found that education positively and significantly affects farmers' decision to adopt computers with Internet access in the U.S. The Pew Research Center survey, conducted among 30,133 people in 27 countries, shows that better-educated people are more likely to be digitally connected (Silver & Cornibert, 2019).

Farm labor has a positive and statistically significant marginal effect. The finding suggests that one more farm labor increase in a household tends to increase the probability of ICT adoption by 1.8%. Labor is an important factor in agricultural production, and ICT adoption helps improve farm labor productivity via disseminating agriculture-related information (Kaila & Tarp, 2019; Zhang, Wang, & Duan, 2016). ICT adoption is also positively associated with asset ownership, such as cars and indoor toilets. We show that car ownership and indoor toilet ownership increase the likelihood of ICT adoption by 21% and 9.2%, respectively. To some extent, cars and indoor toilets are treated as a symbol of wealth in many rural areas of developing countries, including China and India, and only wealthy farm households can afford them. Silver and Cornibert (2019) revealed that income level plays a sizable role in explaining technology adoption differences. Therefore, higher-income households are more likely to use ICTs such as computers and mobile phones.

The negative and significant marginal effect of the pension variable suggests that compared to farmers not receiving the pension, those who received it are 6% less likely to adopt ICTs. This is because pension receivers are usually old generations. Being a specialized agricultural producer increases the probability of ICT adoption by 5.7%. Specialized producers mainly seek profit maximization from agricultural production, while ICT adoption can help them realize market opportunities, enhance bargaining power in market transactions, reduce transaction costs, and also obtain information on weather conditions and extension information. The positive role of ICT adoption in agricultural production has also been recorded in previous studies (Cette, Nevoux, & Py, 2021; Kaila & Tarp, 2019; Laddha, Tiwari, Kasperowicz, Bilan, & Streimikiene, 2022; Nikam et al., 2022). In addition, compared to the farmers living in western China (reference group), those living in the central and eastern regions are 2.2% and 2.8% more likely to adopt ICTs. The findings suggest that ICT adoption varies across regions primarily due to the differences in rural infrastructure and socio-economic conditions. Finally, the marginal effect of the IV is positive and statistically significant, confirming that an individual's ICT adoption decision is positively influenced by the average number of other ICT adopters within the same county due to spatial peer effects.

5.1.2 | Determinants of access to credit

The results for the determinants of credit access are presented in the third column of Table 3. ICT adoption increases the probability of access to credit by 12.8%.[2] The finding is consistent with Munyegera and Matsumoto (2018), who concluded that using mobile money services increases the likelihood of obtaining a loan for Uganda's rural households. For comparison purposes, we also estimate the impact of ICT adoption on access to credit using a simple probit model and present the results in the last column of Table 3. The results show that ICT adoption increases the likelihood of credit access by 3.3%, which is much smaller than the magnitude observed in the RBP model. This is because the simple probit model treats all explanatory variables as exogenous variables, while we find the presence of selection bias arising from unobserved factors (see significant $\rho_{\tau\epsilon}$ in the lower part of Table A2). Thus, the RBP model estimation provides more reliable results.

Our estimates indicate that age is positive and significant among other control variables, while its squared term is negative and significant. The findings suggest the presence of the life-cycle effect of age on access to credit. We show that older farmers are more likely to acquire credit, with the largest effect occurring at 36 years. Beyond 36, age has a negative effect on farmers' decisions to access credit. The nonlinear relationship between age and access to credit is also confirmed by a study of Indonesian farmers (Okten & Osili, 2004). Compared with older farmers, younger ones usually face credit constraints because they take time to accumulate wealth. The significant and negative marginal effect of the education variable suggests that people receiving middle-level school and college education, respectively, are 5% and 10.6% less likely to access credit. Farmers with better education can be better engaged in higher-income-generating activities such as farm and off-farm works (Abate et al., 2016; Ma et al., 2018; Rahut, Jena, Ali, Behera, & Chhetri, 2015), and thus, they are less likely to be capital constrained.

The marginal effect of farm labor is positive and statistically significant, suggesting that households with more farm labor endowments are 2.2% more likely to access credit. Enough labor endowments enable households to easily allocate surplus labor to farm/off-farm businesses (Rahut & Scharf, 2012), but this requires complementary funds. Households owning a car are 4.4% less likely to access credit on average. Since car ownership is a symbol of wealth, households with cars usually have no capital constraints, and thus, they are less likely to access credit.

The pension variable has a negative and significant impact on access to credit. Compared with households without retirement pensions, those with the pension are 6.7% less likely to obtain credit. The finding confirms that the social pension program helps relieve credit-constraints of rural households. Farmers specializing in agricultural production are 4.4% more likely to access credit. This may be because those households specializing in agriculture require credit to purchase yield-enhancing inputs (e.g., fertilizers, pesticides, and improved seeds) and crop insurance. Compared to the households in western China (reference group), those living in the central and eastern regions are 4.6% and 15.3%, respectively, less likely to access credit. The findings suggest the existence of location-fixed effects that affect rural farmers' decision to access credit.

5.1.3 | Disaggregated effects of ICT adoption (heterogeneity analysis)

To better understand the heterogeneity effects of ICT, we disaggregate the impact of ICT adoption on access to credit by gender of household head and geographical location (Table 4). For

TABLE 4 Disaggregated marginal effects of ICT adoption on access to credit by gender and geographic locations

Category	Observations	Marginal effects
Gender		
Male	4,435	0.130 (0.041)***
Female	3,336	0.146 (0.056)***
Geographic locations		
West	2,410	0.318 (0.088)***
Central	2,091	0.202 (0.061)***
East	3,270	0.031 (0.062)

Note: Standard errors in parentheses.

Abbreviation: ICT, information and communication technology.

***$p < 0.01$.

the sake of simplicity, the marginal effects of other control variables are not presented, but they are available upon request.

The results show that the effects of ICT adoption on access to credit are heterogeneous between male and female household heads. ICT adoption effect on access to credit is larger for women than for men. Specifically, ICT adoption increases the probability of credit access for women by 14.6%, while it increases the likelihood of credit access for men by 13%. Several studies have reported that ICT adoption empowers rural women in terms of education and knowledge creation (i.e., the combination, transfer, and conversion of different kinds of knowledge), poverty alleviation, and employment opportunities (Islam, 2015; Umrani & Ghadially, 2003; Yu & Cui, 2019). Our results provide clear evidence that ICT adoption empowers rural women to access credit.

Regarding the disaggregated effects of regions, we find that ICT adoption increases the probability of credit access for rural households in the western and central regions by 31.8% and 20.2%, respectively. In comparison, ICT adoption does not significantly impact credit access of rural households living in the eastern region. In China, the east is economically more developed than the west, so the eastern farm households are less likely to be credit-constrained. Therefore, the findings suggest that ICT adoption empowers farm households to access credit in the relatively less-developed western region.

5.2 | Joint effects of ICT adoption and access to credit on household income

5.2.1 | Results of the selectivity-corrected OLS model estimation

Table 5 presents the joint effects of ICT adoption and access to credit on household income. As indicated previously, the selectivity-corrected OLS model is used to estimate Equation 4, in which the predicted ICT adoption variable and predicted access to credit variable from the SUBP model estimates (see Table A3)[3] are used to control for their endogeneity issues. The selectivity-corrected OLS model estimation results are presented in the second column of Table 5. We find that ICT adoption has a positive and statistically significant impact on

TABLE 5 Joint effects of ICT adoption and access to credit on household income

Variables	Selectivity-corrected OLS
ICT adoption (predicted)	2.907 (0.358)***
Access to credit (predicted)	−8.976 (3.971)**
Age	0.324 (0.109)***
Age squared	−0.004 (0.002)***
Gender	0.374 (0.312)
Primary school	−1.157 (0.433)***
Middle-level school	−0.880 (0.584)
College and above	2.400 (1.344)*
Farm labor	−0.628 (0.302)**
Car ownership	4.984 (0.521)***
Indoor toilet	2.046 (0.376)***
Pension	−0.189 (0.986)
Soil quality	−0.438 (0.353)
Specialization	2.974 (0.872)***
Central	0.128 (0.601)
East	−0.959 (1.628)
Constant	1.581 (2.184)
Observations	7,771

Note: Standard errors in parentheses; the reference region is west; The dependent variable refers to household income, which is measured at 1,000 Yuan/capita. The reference education level is illiteracy.

Abbreviations: ICT, information and communication technology; OLS, ordinary least square.

*$p < 0.1$. **$p < 0.05$. ***$p < 0.01$.

household income. ICT adoption enables rural households to generate income by enhancing agricultural investments and productivity (which usually transfers to a higher farm income), facilitating off-farm work participation, and stimulating remittance-receiving (Laddha et al., 2022).

Access to credit has a negative and statistically significant impact on household income. This finding contradicts previous studies that showed a positive association between access to credit and a higher household income (Kumar et al., 2020; Luan & Bauer, 2016). To find out the reason, we further estimate Equation 4 by replacing household income, that is, the dependent variable, with farm income and business income. Our results (Table A4) show that access to credit does not significantly impact both farm and business income. The findings reflect that rural credit users may use the acquired credit to cover expenses such as health care, consumption, and children's tuition fees rather than using it for income-generating activities such as purchasing yield-increasing inputs or investing in the off-farm business. Among other factors, we show that household income is also affected by age, ownership of household assets, and agricultural specialization. For example, the significant and positive coefficient of specialization variable suggests that agricultural specialization increases household income, consistent with previous studies (Rae & Zhang, 2009).

TABLE 6 Results of the UQR model estimation

| Variables | Selected quantiles (dependent variable = household income) | | | | |
	10th	30th	50th	70th	90th
ICT adoption (predicted)	0.770***	1.497***	2.606***	2.869***	8.511***
	(0.105)	(0.156)	(0.232)	(0.333)	(1.428)
Access to credit (predicted)	−1.764***	−1.900	−0.669	−4.705	−4.992
	(0.524)	(1.645)	(2.677)	(4.236)	(21.246)
Control variables	Yes	Yes	Yes	Yes	Yes
Constant	−2.335***	−1.204	1.818	4.842**	7.100
	(0.503)	(0.912)	(1.434)	(2.162)	(10.253)
Observations	7,771	7,771	7,771	7,771	7,771

Note: Standard errors in parentheses. Household income is measured at 1,000 Yuan/capita.

Abbreviations: ICT, information and communication technology; UQR, unconditional quantile regression.

**p < 0.05. ***p < 0.01.

5.2.2 | Results of the UQR model estimation

We further check how ICT adoption and credit access affect household income distributions to provide granular insights. Both the conditional quantile regression (CQR) and UQR models have been applied in previous studies (Gregory & Zierahn, 2022; Ma & Zheng, 2022). Compared with the CQR model, whose quantiles are defined conditional on the selected covariates, we can freely add or delete covariates without redefining the quantiles in the UQR model. Thus, we employ the UQR model for empirical purposes and report the results estimated at the 10th, 30th, 50th, 70th, and 90th quantiles. Table 6 presents the estimated results.

The results show that ICT adoption and access to credit affect household income heterogeneously. ICT adoption affects household income positively and significantly. The estimated effects are monotonously increasing at the selected quantiles, and the largest positive effect occurs at the highest 90th quantile. The findings suggest that richer households tend to benefit more from ICT adoption than their poor counterparts. Access to credit affects household income negatively, and the estimated effect is the largest and statistically significant at the lowest 10th quantile.

6 | CONCLUSION AND POLICY IMPLICATIONS

Using the 2016 CLDS data, this study examines the impact of ICT adoption on access to credit and the joint effects of ICT adoption and access to credit on household income. Since both observed and unobserved factors may affect farmers' decisions to become ICT adopters or non-adopters, an RBP model is used to address the selection bias issue associated with ICT adoption. Furthermore, a selectivity-corrected OLS model is applied to estimate the joint effects of ICT adoption and access to credit on household income.

The results of the RBP model reveal a negative selection bias due to unobserved factors. After controlling for this selection bias, we show that ICT adoption increases the probability of credit access by 12.8%. In addition to ICT adoption, we find that age, education, farm labor, car

ownership, retirement pension, and agricultural specialization affect farmers' decision to access credit. ICT adoption is mainly determined by gender, education, farm labor, ownership of cars and indoor toilets, pension, and agricultural specialization. The disaggregated analyses reveal that the impacts of ICT adoption on access to credit are heterogeneous between male- and female-headed households and among geographical locations. We show that ICT adoption better facilitates credit access for rural women and farm households in relatively less-developed regions. The additional analysis suggests that access to credit does not significantly impact ICT adoption, confirming that farmers usually do not use acquired credit to purchase relatively luxury ICT devices such as computers and smartphones. In addition, the selectivity-corrected OLS model estimates show that ICT adoption and access to credit affect household income differently. We find that ICT adoption significantly increases household income, but access to credit shows a negative effect primarily because farmers may not invest the obtained credit in income-generating activities. The UQR model estimates show that ICT adoption has the largest positive impact on household income at the 90th quantile.

Our finding generally confirms the significant role of ICT adoption in facilitating rural farmers' access to credit in the digital age. This suggests that the government should make further efforts to improve rural ICT infrastructure, enhance farmers' ICT adoption, and improve the poor's access to credit. Since the rural financial markets are not gender-neutral, developing rural credit programs should consider gendered differences in access to credit. We find that access to credit is negatively associated with farm income, business income, and household income. The findings suggest that the government should help rural households obtain credit for investments in income-generating farm and off-farm activities, especially in the regions where financial and credit markets are not well developed. Because mobile money can make loan borrowing much faster and more convenient, innovative policies and strategies should consider developing ICT-based financial products to enable households to access sufficient funds for farm and off-farm business investments, which can help improve rural household welfare. Rural women should be given special attention when implementing ICT-based programs for rural credit access.

The present study is subject to some limitations. First, due to data limitations, we are unable to distinguish the different impacts of formal versus informal credit access on ICT adoption or investigate the influence of ICT adoption on the loan amount. Second, rural households may use the acquired credit to invest in income-generating farm and off-farm activities or use it to satisfy basic household expenses. However, we cannot have a deep exploration due to the absence of relevant data. Third, our empirical analyses are based on 1-year cross-sectional data so we cannot capture the dynamic relationships between ICT adoption, access to credit, and household income. Nevertheless, we believe these are promising areas for future studies when the required data are available.

CONFLICT OF INTEREST

There is no conflict of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from Wanglin Ma upon request.

ORCID

Wanglin Ma [ID] https://orcid.org/0000-0001-7847-8459

ENDNOTES

[1] The fewer products the farm produces the more specialized it is (Czyżewski & Smędzik-Ambroży, 2015). The opposite of specialization of production is its diversification.

[2] Figure 2 in Section 2 also suggests that there may exist a reverse causality between ICT adoption and access to credit. To investigate this issue, we estimated the impact of access to credit on ICT adoption and found that access to credit does not significantly affect farmers' decisions of ICT adoption. This is not implausible, given the fact that farmers may use the acquired credit to deal with uncertainties in life (e.g., sickness and natural disasters) and pay for life necessities (e.g., foods, children's tuition fees, and social interactive–oriented gift money) rather than purchase luxury goods (e.g., smartphones and computers).

[3] In the SUBP model estimation, the synthesized IV (see discussions in Section 3.1) is used in the ICT adoption equation and another IV representing gift money (see the lower part of Table 1) is used in access to credit equation for model identification.

Abbreviation: ICT, information and communication technology.

* $p < 0.1$.

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APPENDIX

TABLE A1   The results of Pearson correlation analysis

Variables	Access to credit	ICT adoption	IV_County_level
Access to credit	1.000		
ICT adoption	0.0483***	1.000	
IV	−0.011	0.410***	1.000

Abbreviations: ICT, information and communication technology; IV, instrumental variable.
***$p < 0.01$.

TABLE A2   Coefficient estimation of the effects of ICT adoption on access to credit

| Variables | RBP model | | Probit model |
	ICT adoption (coefficients)	Access to credit (coefficients)	Access to credit (coefficients)
ICT adoption		0.376 (0.100)***	0.096 (0.035)***
Age	−0.013 (0.007)*	0.026 (0.006)***	0.024 (0.006)***
Age squared	−0.000 (0.000)*	−0.000 (0.000)***	−0.000 (0.000)***
Gender	−0.185 (0.035)***	0.014 (0.033)	−0.003 (0.032)
Primary school	0.139 (0.049)***	−0.047 (0.045)	−0.033 (0.045)
Middle-level school	0.427 (0.051)***	−0.147 (0.050)***	−0.101 (0.048)**
College and above	0.644 (0.125)***	−0.312 (0.102)***	−0.256 (0.101)**
Farm labor	0.062 (0.016)***	0.064 (0.016)***	0.067 (0.016)***
Car ownership	0.729 (0.049)***	−0.129 (0.050)***	−0.059 (0.044)
Indoor toilet	0.320 (0.034)***	−0.003 (0.034)	0.032 (0.032)
Pension	−0.208 (0.062)***	−0.196 (0.059)***	−0.209 (0.059)***
Soil quality	−0.123 (0.033)***	−0.023 (0.031)	−0.042 (0.031)
Specialization	0.197 (0.070)***	0.129 (0.064)**	0.149 (0.063)**
Central	0.076 (0.043)*	−0.126 (0.039)***	−0.121 (0.039)***
East	0.096 (0.042)**	−0.446 (0.039)***	−0.412 (0.037)***
IV	2.084 (0.086)***		
Constant	−0.485 (0.184)***	−0.660 (0.167)***	−0.479 (0.157)***
$\rho_{\tau\varepsilon}$	−0.182 (0.061)***		
Wald test of $\rho_{\tau\varepsilon} = 0$	8.449, Prob $> \chi^2 = 0.004$		
Observations	7,771		7,771

Note: Standard errors in parentheses. The reference region is west. The reference education level is illiteracy.
Abbreviations: ICT, information and communication technology; IV, instrumental variable.
*$p < 0.1$. **$p < 0.05$. ***$p < 0.01$.

TABLE A3 SUBP model estimation

Variables	ICT adoption (coefficients)	Access to credit (coefficients)
Age	−0.013 (0.007)*	0.023 (0.006)***
Age squared	−0.000 (0.000)*	−0.000 (0.000)***
Gender	−0.188 (0.035)***	−0.007 (0.032)
Primary school	0.143 (0.049)***	−0.029 (0.045)
Middle-level school	0.431 (0.051)***	−0.087 (0.047)*
College and above	0.655 (0.126)***	−0.243 (0.101)**
Farm labor	0.060 (0.016)***	0.068 (0.016)***
Car ownership	0.729 (0.049)***	−0.036 (0.044)
Indoor toilet	0.317 (0.034)***	0.045 (0.032)
Pension	−0.209 (0.062)***	−0.213 (0.059)***
Soil quality	−0.122 (0.033)***	−0.048 (0.031)
Specialization	0.200 (0.070)***	0.154 (0.063)**
Central	0.071 (0.043)*	−0.119 (0.039)***
East	0.095 (0.042)**	−0.396 (0.037)***
IV	2.077 (0.087)***	
Gift money		−0.001 (0.000)*
Constant	−0.493 (0.184)***	−0.399 (0.157)**
$\rho'_{\tau\varepsilon}$	0.037 (0.022)*	
Wald test of $\rho'_{\tau\varepsilon}=0$	2.957, Prob $>\chi^2 = 0.086$	
Observations	7,771	

Note: Standard errors in parentheses. The reference region is west. The reference education level is illiteracy.

Abbreviations: ICT, information and communication technology; IV, instrumental variable.

*$p < 0.1$. **$p < 0.05$. ***$p < 0.01$.

TABLE A4 Joint effects of ICT adoption and access to credit on farm income and business income: Selectivity-corrected OLS estimations

Variables	Farm income (coefficients)	Business income (coefficients)
ICT adoption (predicted)	0.006 (0.185)	1.424 (0.209)***
Access to credit (predicted)	−5.920 (2.054)***	−4.689 (2.321)**
Age	0.159 (0.056)***	0.151 (0.063)**
Age squared	−0.003 (0.001)***	−0.002 (0.001)**
Gender	0.110 (0.161)	0.381 (0.182)**
Primary school	−0.275 (0.224)	−0.658 (0.253)***
Middle-level school	−0.428 (0.302)	−0.945 (0.341)***
College and above	−1.329 (0.695)*	−0.879 (0.786)
Farm labor	1.426 (0.156)***	−0.283 (0.177)
Car ownership	0.998 (0.270)***	2.038 (0.305)***
Indoor toilet	−0.727 (0.195)***	0.571 (0.220)***
Pension	−1.941 (0.510)***	−1.399 (0.576)**
Soil quality	−0.025 (0.183)	−0.290 (0.206)
Specialization	4.837 (0.451)***	1.000 (0.510)**
Central	−0.666 (0.311)**	−0.644 (0.351)*
East	−2.155 (0.842)**	−1.674 (0.951)* y
Constant	−1.219 (1.130)	−1.712 (1.277)
Observations	7,771	7,771

Note: Standard errors in parentheses. Both farm income and business income are measured at 1,000 Yuan/capita. The reference education level is illiteracy. The reference region is west.

Abbreviations: ICT, information and communication technology; OLS, ordinary least square.

*$p < 0.1$. **$p < 0.05$. ***$p < 0.01$.