Journal of Integrative Agriculture 2022, 21(1): 282–292

Available online at www.sciencedirect.com

ScienceDirect

RESEARCH ARTICLE

Does Internet use promote the adoption of agricultural technology? Evidence from 1 449 farm households in 14 Chinese provinces

ZHENG Yang-yang[1], ZHU Tie-hui[2], JIA Wei[2]

[1] *College of Economics and Management, Nanjing Forestry University, Nanjing 2100372, P.R.China*
[2] *Institute of Agricultural Economics and Development, Chinese Academy of Agricultural Sciences, Beijing 100081, P.R.China*

Abstract

China is characterized as 'a large country with many smallholder farmers' whose participation in modern agriculture is key to the country's modern agriculture development. Promoting smallholder farmers' adoption of modern agricultural production technology is one effective way to improve the capabilities of smallholder farmers. This paper aims to explore the impact of Internet use on the adoption of agricultural production technology by smallholder farmers based on a survey of 1 449 smallholders across 14 provinces in China. The results suggest that Internet use can significantly promote technology adoption, with the probability of adopting new crop varieties, water-saving irrigation technology and straw-returning technology increasing by 0.200, 0.157 and 0.155, respectively. Furthermore, the effect of Internet use is found to be heterogeneous with a greater effect on smallholder farmers having low education levels, limited training, and high incomes. To increase agricultural production technology adoption by smallholders, rural Internet infrastructure and Internet use promotion should be the focus for the Chinese government.

Keywords: Internet use, smallholder farmers, agricultural technology adoption

1. Introduction

Building the connection between smallholder farmers and modern agriculture is key to rural revitalization and an important component of agricultural modernization. Numerous studies have examined approaches that promote the connection, such as improving the organization of smallholder farmers and agricultural socialized services, and implementing specific models such as land trusteeship, land stock cooperatives and 'new agricultural business entities+smallholder farmers' (He and Wu 2019; Ye and Zhang 2020). However, existing literatures primarily focus on external drivers, that is, they pay more attention to providing services to smallholder farmers than building the capabilities of smallholder farmers. The adoption of advanced agricultural technology is an important means to build smallholder farmers' capacity. On the one hand, adopting advanced agricultural technology can change the traditional farming methods of smallholder farmers, optimize the allocation of agricultural production essential factors, reduce agricultural production costs, and improve agricultural production efficiency (Muzari *et al*. 2012; Wossen *et al*. 2019). On the other hand, advanced

Received 24 December, 2020 Accepted 24 May, 2021
Correspondence ZHU Tie-hui, E-mail: zhutiehui@caas.cn; JIA Wei, E-mail: jiawei@caas.cn

doi: 10.1016/S2095-3119(21)63750-4

production technologies contribute to achieving the goal of green agricultural development by reducing water use or improving soil quality (Asfaw *et al*. 2012). Moreover, the adoption of agricultural production technology can create more market opportunities and increase income, thereby breaking the poverty trap and promoting economic growth (Asfaw *et al*. 2010; Wossen *et al*. 2015, 2017). Schultz (1964) pointed out in *Transformation of Traditional Agriculture* that the key to transforming traditional agriculture is to introduce modern production technologies.

To effectively promote smallholder farmers' adoption of advanced agricultural technologies, it is necessary to identify the key barriers of the adoption. Limited access to information is considered as the main obstacle. The probability of adopting new technology decreases significantly if farmers lack information about the benefits or how to correctly use the technology (Jack 2013). Aker (2010) believed that information supply and technology supply are equally important in the process of promoting agricultural technology. Therefore, how to enable farmers to obtain technical information conveniently and reduce information asymmetry becomes an important research question (Qiu *et al*. 2016). The Internet, as an important means for smallholder farmers to obtain information, has a profound impact on the behavior and thinking of smallholder farmers. First, the Internet can reduce farmers' information search cost, enabling them to obtain technical information in a timely and convenient manner. The Internet also enhances farmers' understanding of the 'risk-benefit aspects' of agricultural technology, and breaks the traditional impression of production technology (Genius 2006). Second, Internet use can increase the bargaining power of smallholder farmers, expand the agricultural sales market, improve agricultural production performance, and in turn encourage farmers to adopt new technologies (Aker and Ksoll 2016; Donovan 2017). Third, Internet use can improve the management and learning capabilities of smallholder farmers, enhance their skilled human capital, and increase their income (Gao 2018; Leng *et al*. 2020). In addition, the Internet has established an effective platform for sharing and disseminating environmental protection concepts, policies and knowledge, which has increased farmers' awareness of environment protection literacy. Farmers with different levels of knowledge can equitably obtain and exchange environmental knowledge through the Internet, and post their comments on current environmental issues (Peng *et al*. 2019; Gong *et al*. 2020).

Exploring the use of the Internet has important theoretical and policy implications for technology adoption by smallholder farmers. Studying the role of Internet use in promoting technology adoption by smallholder farmers both enriches the smallholder production theory and expands the boundaries of the Information and Communication Technology (ICT) research. According to the *Third National Agricultural Census* in 2016, the number of smallholder farmers in China accounted for more than 98% of the total rural households, and the area of arable land operated by smallholder farmers accounted for 70% of the total arable land. Therefore, investigating agricultural technology adoption by smallholder farmers is of great significance to agricultural modernization in China. This paper is innovative in a number of ways. First, it focuses on how to achieve the connection between Internet use and agricultural technology choice through capacity building of smallholder farmers rather than through merely providing external supports. Second, different from other studies, this study examines agricultural technology adoption before, during and after production, respectively, as well as the heterogeneous effect of Internet use on technology adoption. Third, the study uses a unique survey data collected by the National Agricultural and Rural Development Research Institute, China Agricultural University. The sample size is large (N=1 449) and representative, covering 14 provinces/autonomous regions of China.

2. Theoretical framework

This paper draws on the theoretical framework of Yoav and Shchori-Bachrach (1973), and incorporates 'information' as an input factor into the production function of farmers. The function is given as follows:

$$Y_t=g(K_t)F(L, N_t) \tag{1}$$

where Y_t is the output in period t, L is land input, and N_t is other input in period t, such as new crop varieties, soil, fertilizer, etc., K_t is the accumulated information during t, g and F are concave functions. Assuming $F(\cdot)$ has a constant return to scale, the function is defined as follows:

$$y_t=g(K_t)\cdot f(n_t) \tag{2}$$

where $y_t=Y_t/L$; $n_t=n_t/L$; $f=F(1:n_t)/L$. Assuming that $f(s)$ has good production function characteristics. The hypothesis of Kislev and Shchori-Bachrach (1973) is applicable to the knowledge function $g(\cdot)$, which is the marginal contribution of knowledge is positive and shows a decreasing trend. As knowledge grows, the knowledge function converges to an upper limit $\overline{g}$, which means that with the accumulation of knowledge, the marginal productivity of information increment tends to reach zero. When knowledge is 0, the value of $g(\cdot)$ is very low or even 0.

When defining the cumulative information K_t and its acquisition, it is assumed that farmers obtain it through passive and active learning, and active information collection involves costs such as time or money. It is assumed that the marginal costs of information obtained at any given time are increasing.

The knowledge state (K) at time t is defined as follows:

$$K_t=K_{t-1}+A_t+h_t \quad (3)$$

where h_t describes the information acquired passively during this period of time. h_t may increase over time. The variable A_t indicates the degree of purposeful knowledge acquisition, and the information cost C_t is expressed as follows:

$$C_t=C(A_t) \quad C'>0,\ C''>0 \quad (4)$$

The profit function π of the farmer households with a scale of L is expressed as follows:

$$\pi_t=L\cdot[g(K_t)\cdot f(n_t)-p\cdot n\ ]-C(A_t) \quad (5)$$

Let p denote the price of n, combine eqs. (3) and (5), and obtain the first-order derivation of n and A, respectively:

$$\pi_n=L\cdot[g(K_t)\cdot f'-p]\leq 0 \quad n_t\pi_n=0 \quad (6)$$

$$\pi_\alpha=L\cdot g'\cdot f(n_t)-c'\leq 0 \quad A_t\pi_\alpha=0 \quad (7)$$

where π_n and π_α represent the partial derivatives of profit with regard to n and A, respectively. Assuming that $\pi_n=0$, then $dn/dk_t=-(g'f'/gf'')>0$; it means that the more information farmers obtain, the more likely they are to adopt new technologies. Once a new technology is adopted, as long as the marginal productivity of information (g') is positive, farmers with a higher level of information accumulation will adopt more new technologies. Considering two farmers with the same scale of operation, the framer acquiring more information will adopt new technologies faster than the other. Assuming that the threshold information level K^* when $g(K)=\overline{g}$, $K=K^*$ is within the range of K value, the number of farmers adopting new technologies will increase until K_t exceeds K^*.

3. Data and models

3.1. Data

This study utilized the Survey of Returning Home from January to February 2019 by the National Agricultural and Rural Development Research Institute of China Agricultural University. The enumerators included undergraduate, master and doctoral students among various majors of China Agricultural University[1]. Before data collection, the enumerators were provided trainings to explain the aims, question structures, and key challenges of the questionnaire.[2] A number of researchers were responsible for sending and receiving questionnaires and answering questions encountered during data collection, while returned questionnaires were reviewed by research leaders. The survey questionnaire included two levels, farmer questionnaire and village-level questionnaire. In each village, 15–20 households were randomly selected. The survey obtained 1 952 grain grower questionnaires in total. Since this paper mainly focuses on smallholder farmers, the samples of non-smallholders with land of 30 mu (1 ha=15 mu) and above were excluded, according to the World Bank's classification standards for smallholder farmers[3]. Inconsistent and incomplete questionnaires were also dropped, resulting in a dataset of 1 449 samples from 144 villages in 119 counties/districts of 14 provinces/autonomous regions sparsely located in eastern, central, western and northeastern China (i.e., Inner Mongolia, Jilin, Sichuan, Anhui, Shandong, Jiangsu, Jiangxi, Hebei, Henan, Hubei, Hunan, Gansu, Liaoning and Heilongjiang), demonstrating a good regional representativeness (Table 1). Heilongjiang and Liaoning, as major agricultural production provinces, have relatively few samples. The main reason is that there are more large-scale farmers in Northeast China than in other regions.[4]

3.2. Variable selection

The dependent variables of this study are smallholder farmers' agricultural technology adoption of three technologies: new crop varieties, water-saving irrigation technology and straw-returning technology. New crop varieties refer to those with stronger disease resistance or more obvious yield-increasing effects than general crop varieties, but the price is relatively high. Water-saving irrigation technologies refer to production technologies that can effectively save water, such as sprinkler irrigation, micro-sprinkler irrigation, subsurface irrigation and drip irrigation. Straw-returning technology refers to measures to increase fertility and increase production, which

[1] The questionnaire mainly focuses on the national grain production survey. First, the research team determined the number of samples in each province, region, and city based on the grain production area. Secondly, according to the surveyed counties (cities) corresponding to the corresponding household registration students; the students conduct surveys on the township where the household registration is located, and select about 1–2 villages, about 15 households.

[2] Since all majors of China Agricultural University are related to agriculture, the recruited enumerators have a high level of awareness of agriculture and therefore data collection is of high quality.

[3] The World Bank classifies rural households with an average arable land area of less than 2 hectares (30 mu) as smallholder farmers.

[4] The sample in Heilongjiang is smaller than that in Inner Mongolia. The possible reason is that there are more students participating in the Inner Mongolia survey, and the survey sample may be relatively high.

Table 1 Distribution of samples by province/autonomous region

Province/Autonomous region	Sample size[1)]	Percentage of sample (%)
Inner Mongolia	87	6.00
Jilin	72	4.97
Sichuan	171	11.80
Anhui	38	2.62
Shandong	268	18.50
Jiangsu	130	8.97
Jiangxi	75	5.18
Hebei,	146	10.08
Henan	200	13.80
Hubei	112	7.73
Hunan	61	4.21
Gansu	16	1.10
Liaoning	41	2.83
Heilongjiang	32	2.21
Total	1449	100.00

[1)] The authors count the samples according to the survey.

improve traditional incineration methods and avoid air pollution caused by incineration, including straw crushing and pressing, returning to the field with straw mulching, returning to the field by piles, returning to the field by burning, and returning to the field. Each new technology was assigned a value of 1 if the farmer adopted it, and 0 otherwise.

Internet use is the key independent variable. It is considered that even farmers have smart phones or Internet skills, they may not obtain agricultural information through the Internet. If smallholder farmers were asked directly whether they have smart phones or use the Internet, it may cause measurement errors (Ma and Zhu 2020; Nie *et al*. 2020). The survey directly asked whether farmers use the Internet to obtain agricultural information in order to accurately measure information access through the Internet[5].

This study chose the control variables from three categories: personal characteristics of farmers including age, education level, health status, and training experience (Gao *et al*. 2018; Ma 2020); family characteristics including number of laborers, the proportion of non-agricultural income, quality of cultivated land, farm size, number of plots, household income, and subsidies (Boz 2016; Gao *et al*. 2018); and village characteristics including poverty, economic development level, water source guarantee, and distance to the nearest trunk road (Tatlıdil *et al*. 2009).

As shown in Table 2, farmers adopting water-saving irrigation technology, new crop varieties and straw-returning technology accounted for 28.36, 63.15 and 63.35% of the total sample, respectively. Those who used the Internet to obtain agricultural production information accounted for 14.5% of the total sample. Those who received training accounted for 20.8% of the total sample. The average age of smallholder farmers was 54 years, the average number of family agricultural labor was 2.2, the average farm size was 5.7 mu, and the average annual household income was 56000 CNY (6.5491 CNY=1 USD, according to the latest exchange rate on December 9, 2020). The poverty-stricken villages and villages with guaranteed water sources accounted for 23.4 and 76.1% of the total sample, respectively.

As shown in Table 3, among the smallholder farmers who used the Internet, 76.67% adopted new crop varieties, 43.33% adopted water-saving irrigation technologies, and 73.81% adopted straw-returning technology. Among the smallholder farmers who did not use the Internet, 60.86% adopted new crop varieties, 25.83% adopted water-saving irrigation technologies, and 61.58% adopted straw-returning technology.

3.3. Model selection

Binary probit regression model Since adoption of agricultural technology is a binary choice, the binary probit regression model was used to analyze the influencing factors for smallholder farmers' technology adoption. The model is defined as follows:

$$P=F(Technology=1|X)=1/1+e^{-y} \quad (8)$$

$$Technology_i=\beta_0+\beta_1 Internet_i+z_i\gamma+region_i\delta+\varepsilon_i \quad (9)$$

where $Technology_i$ indicates whether a farmer adopts the agricultural technology; P is the probability of adoption, $Internet_i$ is Internet use, β_1 is the coefficient of Internet use; z_i is a vector of control variables. γ is a vector of the coefficient of the control variables, $region_i$ is a vector of dummy variables for different regions in China, and δ is a vector of coefficients of regional dummy variables.

Endogenous switching model Internet use does not satisfy random sampling, that is, there are systemic differences in the initial conditions before Internet use, and there is a problem of 'self-selection' in Internet use by smallholder farmers. Internet use decision-making is the result of a combination of many factors, and some factors are unobservable, such as farmers' cognition of the Internet. Taking into account the selection bias caused by observable and unobservable factors and being inspired by Abdulai and Huffman (2014) and Ma *et al*. (2018), this study adopted the Endogenous Switching

[5] The questionnaire asked "did you use the Internet to obtain agricultural service information?".

Table 2 Descriptive statistics of variables

Variables		Description	Mean	Standard deviation
Dependent variables	New crop varieties	1 if smallholder farmers adopted it, 0 otherwise	0.631	0.483
	Water-saving irrigation technology	1 if smallholder farmers adopted it, 0 otherwise	0.284	0.451
	Straw-returning technology	1 if smallholder farmers adopted it, 0 otherwise	0.634	0.482
Independent variable	Internet use	1 if smallholder farmers used the Internet to obtain agricultural information, 0 otherwise.	0.145	0.352
Control variables	Age	Age of household head, in years	54.176	11.483
	Education	Junior high school and above=1; primary school and below=0	0.572	0.495
	Health status	Better=1; worse=0	0.947	0.224
	Training	1 if smallholder farmers received training, 0 otherwise	0.208	0.406
	Household labor	Number of family agricultural labor	2.177	1.081
	Non-agricultural income Proportion	The proportion of household non-agricultural income in total household income	0.700	0.312
	Quality of cultivated land	Moderate and above=1; Moderately lower=0	0.788	0.409
	Farm size	Logarithm of farm size (mu)[1)]	1.838	0.671
	Number of plots	Number of plots	4.021	3.624
	Household income	Logarithm of total household income	10.473	1.025
	Subsidies	Logarithm of subsidies in total: agricultural machinery subsidies, subsidies for large grain farmers, production technology subsidies, agricultural insurance premium subsidies, loan discounts, etc. (CNY)	5.438	2.198
	Whether it is a poor village	1 if it was a poor village, 0 otherwise	0.234	0.423
	Economic development level	Moderate and above=1; Moderately lower=0	0.685	0.465
	Water source guarantee	1 if water source was guaranteed, 0 otherwise	0.761	0.427
	Distance or road trunk	Logarithm of the distance (km) to the nearest trunk road	1.593	1.218

[1)] 1 ha=15 mu.

Table 3 Internet use and agricultural technology adoption

	New crop varieties		Water-saving irrigation technologies		Straw-returning technology	
	Sample size	Percentage (%)	Sample size	Percentage (%)	Sample size	Percentage (%)
Internet use and technology adoption	161	76.67	91	43.33	155	73.81
Internet use but no technology adoption	49	23.33	119	56.67	55	26.19
No Internet use but technology adoption	754	60.86	320	25.83	763	61.58
No Internet use and no technology adoption	485	39.14	919	74.17	476	38.42

Model to empirically analyze the impact of Internet use on the adoption of agricultural production technology by smallholder farmers.

In the first stage, the probit model was used to estimate the probability of smallholder farmers' Internet use:

$$Internet_i^*=\alpha+\beta S_i+\mu_i,\ Internet_i=\begin{cases}1,\ if\ Internet_i^*>0\\0,\ if\ Internet_i^*\leq 0\end{cases} \tag{10}$$

where $Internet_i^*$ is an unobservable latent variable. When $Internet_i^*>0$, $Internet_i=1$, that is, farmers use the Internet. S_i is the control variable. In addition to including the variables in Z_i, it also includes the variable 'proportion of households using a computer'. α and β are parameters to be estimated, and μ_i is a random disturbance term.

The second stage estimated the impact of Internet use on technology adoption by smallholder farmers,

When $Technology_i=1$

$$Technology_{1i}^*=\alpha_1+\gamma_1 Z_{1i}+\varepsilon_{1i},$$

$$Technology_{1i}=\begin{cases}1,\ if\ Technology_{1i}^*>0\\0,\ if\ Technology_{1i}^*\leq 0\end{cases} \tag{11}$$

When $Technology_i=0$

$$Technology_{0i}^*=\alpha_0+\gamma_0 Z_{0i}+\varepsilon_{0i},$$

$$Technology_{0i}=\begin{cases}1,\ if\ Technology_{0i}^*>0\\0,\ if\ Technology_{0i}^*\leq 0\end{cases} \tag{12}$$

where $Technology_{1i}$ and $Technology_{0i}$ respectively represent the adoption of agricultural production technology by small farmers who use the Internet and those who do not use the Internet. α_1, α_0, γ_1, γ_0 represent parameters to be estimated, and ε_{1i}, ε_{0i} represent random disturbance items.

Based on the eqs. (11) and (12), the agricultural production technology adoption of small farmers using the Internet can be written as eq. (13), and the counterfactual model can be expressed as eq. (14).

$$E(Technology_{1i}|Technology_i=1)=\alpha_1+\gamma_1 Z_{1i}+\varepsilon_{1i} \quad (13)$$

$$E(Technology_{0i}|Technology_i=1)=\alpha_0+\gamma_{01} Z_{0i}+\varepsilon_{0i} \quad (14)$$

The average treatment effect on the treated (ATT) of the agricultural production technology adopted by small farmers using the Internet can be expressed as the difference between eq. (13) and eq. (14).

$$ATT=E(Technology_{1i}|Technology_i=1)-E(Technology_{0i}|Technology_i=1) \quad (15)$$

4. Results and discussion

Firstly, using a probit model, this paper estimated the baseline impact of Internet use on the adoption of agricultural production technology of smallholder farmers. Secondly, based on farmers' education level, training and income, the heterogeneous influence of Internet use on farmers' agricultural production technology adoption was estimated. Finally, the Endogenous Switching Model was used to address the self-selection problems of Internet use.

4.1. Baseline regression

As shown in Table 4, multi-collinearity check was conducted to obtain a variance inflation factor of 1.28, indicating that there is no serious multi-collinearity among the independent variables. The regression coefficients showed that Internet use increased the probability of adopting new crop varieties, water-saving irrigation technology and straw-returning technology by 0.200, 0.157 and 0.155, respectively. As an important means for information acquisition, Internet use can help farmers obtain more market information, technical information and policy information. In neoclassical economics, the market is perfect and fully competitive. However, in reality, farmers face information asymmetry and market price fluctuations as sellers. Farmers must consider where the agricultural products are sold, how they are sold, and to whom they sell in order to maximize profit. According to Transaction Cost Theory, information search cost is an important part of transaction costs, and reducing information search costs can increase sales in farmers' markets performance, promoting the adoption of agricultural technology for smallholder farmers (Tadesse and Bahiigwa 2015). For example, smallholder farmers can obtain price information timely through the Internet and make judgments on future price trends, which reduces information asymmetry and market risk, and consequently the risk of agricultural technology adoption. Similarly, through the Internet, smallholder farmers can timely and accurately understand the potential risks and benefits of new technologies, and master the application and operation of new technologies, thereby reducing the risks and uncertainties of new technologies. In addition, smallholder farmers can obtain more agricultural policy information through the Internet. Especially under the background of Rural Vitalization Strategy, Internet use can enhance farmers' policy awareness and explore market opportunities based on the latest agricultural policies, thus stimulating smallholder farmers' agricultural technology adoption. In addition, Internet use had a greater effect on the adoption of new crop varieties than on that of the other two technologies, which may be due to the more obvious effect of new crop varieties on crop yield and income. Specifically, compared with the other two technologies, smallholder farmers pay more attention to the relevant information about new crop varieties and can obtain more information on new crop varieties by using the Internet. For control variables at the individual level, the effect of age on the adoption of water-saving irrigation technology was significantly negative. This may be due to the fact that older people are more reluctant to accept new information and adopt new technology than their younger counterparts. The effect of education on the adoption of water-saving irrigation technology was significantly negative, which may be due to the fact that farmers with higher education levels are more engaged in non-agricultural employment, and thus show less willingness to invest in agricultural productions. Training had a significant and positive impact on the adoption of water-saving irrigation technology and straw-returning technology. This is expected as training can increase farmers' understanding of agricultural production technologies and increase their capacity of implementing these technologies (Jia *et al*. 2013).

Regarding the household-level controls, the more labor a household had, the greater the probability of it adopting straw-returning technology. One possible reason is that a certain amount of labor is needed to implement the technology. The proportion of non-agricultural income had a significantly negative impact on the adoption of new crop varieties and straw-returning technology. The reason may be that the higher the proportion of non-agricultural income, the less time, labor and capital smallholder farmers spend on agriculture. This is contrary to the

Table 4 Regression results: The impact of Internet use on the of agricultural technology choice1)

	New crop varieties	Water-saving irrigation technologies	Straw-returning technology
	dy/*dx*	*dy*/*dx*	*dy*/*dx*
Internet use	0.200***	0.157***	0.155***
	(0.038)	(0.032)	(0.035)
Age	0.0004	–0.004***	0.002
	(0.001)	(0.001)	(0.001)
Education level	0.041	–0.074***	–0.030
	(0.027)	(0.025)	(0.025)
Health status	–0.025	–0.032	0.012
	(0.056)	(0.051)	(0.049)
Training	0.005	0.064**	0.074**
	(0.031)	(0.028)	(0.029)
Household labor	–0.019	0.002	0.025**
	(0.012)	(0.011)	(0.011)
Non-agricultural income proportion	–0.100*	–0.043	–0.165***
	(0.0513)	(0.047)	(0.047)
Quality of cultivated land	0.170***	0.067**	0.051*
	(0.029)	(0.029)	(0.027)
Farm size	–0.067***	0.061***	–0.010
	(0.023)	(0.021)	(0.021)
Number of plots	0.016***	–0.0006	–0.009***
	(0.004)	(0.004)	(0.003)
Household income	0.006	–0.027*	0.035**
	(0.015)	(0.014)	(0.014)
Subsidies	–0.0007	–0.029***	0.011**
	(0.006)	(0.005)	(0.005)
Poor village	–0.020	0.038	–0.128***
	(0.0330)	(0.0302)	(0.030)
Economic development level	0.039	0.061**	0.184***
	(0.030)	(0.028)	(0.025)
Water source	–0.034	0.118***	0.083***
	(0.030)	(0.029)	(0.027)
Road trunk distance	0.062***	0.047***	–0.053***
	(0.011)	(0.009)	(0.009)
Eastern reference group			
Middle region	–0.098***	–0.032	0.002
	(0.030)	(0.028)	(0.027)
Western region	–0.033	0.048	–0.253***
	(0.037)	(0.036)	(0.036)
Northeast region	–0.087*	–0.191***	–0.240***
	(0.047)	(0.032)	(0.045)

1) *dy*/*dx* means marginal effects.
Standard errors are shown in brackets. ***, ** and * are significant at 1, 5 and 10% levels, respectively.

finding of Issahaku and Rahaman (2019) that farmers' increased income through non-agricultural employment can promote their adoption of sustainable production measures. It is also a common expectation that the more high-quality cultivated land the households have, the more likely they are to adopt new technologies. However, this study found that larger farm size would reduce the probability of adopting new crop varieties and water-saving irrigation technology. This is in line with Hu *et al*. (2019) that higher cost and risk associated with larger land may reduce farmers' willingness of adopting new technologies. A few family-level controls had mixed influences on the adoption of new technologies. For example, the number of plots had a positive impact on the adoption of new crop varieties while having a significantly negative effect on the adoption of straw-returning technology. The possible reason is that the more scattered the number of land parcels, the lower the land income; therefore, smallholder farmers with a large number of plots are more likely to adopt new crop varieties to improve land productivity. Meanwhile, the more dispersed the land, the higher the cost of straw returning. Similarly, household income had a significantly negative effect on the adoption of water-saving irrigation technology but a positive effect on the adoption of straw-returning technology. It is assumed that high family income is largely due to off-farm employment. This means that high income families have less labor and time to be spent on agriculture, and thus are lacking the amount of labor required by water-saving irrigation technology. However, higher income promotes the adoption of straw-returning technology because it improves the risk resilience of smallholder farmers (Carter *et al*. 2016). The impact of subsidy on the adoption of water-saving irrigation technology was significantly negative, while that on the adoption of straw-returning technology was positive. The possible reason is that the water-saving irrigation technology requires sufficient funds while the straw-returning technology does not.

Regarding the village-level controls, living in a poor village had a significantly negative impact on the adoption of straw-returning technology, which may be due to their financial constraints. It was also found that the higher the level of economic development, the higher the probability of adopting water-saving irrigation technology and straw-returning technology. It is intuitive that farmers living in villages with better economic conditions have a higher level of awareness of new technologies than those in villages with worse economic conditions. Compared with smallholders in the eastern region, the probability of adopting new crop varieties in the middle region was reduced by 0.098, the probability of adopting straw-returning technology in the western region was reduced by 0.253, and the probability of adopting new crop varieties, water-saving irrigation technology and straw-returning technology in the northeastern region was decreased by 0.087, 0.191, and 0.240, respectively. The possible reason is that the eastern region has higher income, more advanced production concepts, and more inclined to adopt production technology than other regions. The land output in the western region is relatively low. In order to reduce production costs, farmers are unwilling to adopt the technology of straw-returning technology. Smallholders may plant corn, wheat or rice at the same time, which makes it difficult to distinguish them by crop type. Therefore, this paper does not divide samples by crop types.

4.2. Heterogeneity analysis

The heterogeneous impact of Internet use on adoption of agricultural production technology was investigated from three aspects: smallholder farmers' education, training and income (Tables 5–7). In terms of education, this paper classified primary schooling and below as a low education level, and junior high schooling and above as a high education level. The marginal effects of Internet use for the low education group were significantly higher than that of the high education group. This indicated that farmers with low education level had limited access to information and lacked agricultural production technology information. The use of the Internet can significantly enrich farmers' information resources and promote the adoption of modern production technology. As Hojo (2002) put forward, agricultural production technology adoption varied across education levels. Farmers with an average or low education level had a higher probability of technology adoption than those with a higher education level.

In terms of training, the marginal effects of Internet use among the trained smallholder farmers were significantly higher than that of the untrained ones. One explanation

Table 5 Heterogeneity analysis on farmers' education characteristics

	New crop varieties		Water-saving irrigation technologies		Straw-returning technology	
	High education level	Low education level	High education level	Low education level	High education level	Low education level
Internet use	0.173***	0.227***	0.121***	0.150***	0.140***	0.171***
	(0.045)	(0.068)	(0.037)	(0.056)	(0.042)	(0.061)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
N	828	621	828	621	828	621

Standard errors are shown in brackets. ***, significant at 1% level.

Table 6 Heterogeneity analysis on farmers' training characteristics

	New crop varieties		Water-saving irrigation technologies		Straw-returning technology	
	Training	No training	Training	No training	Training	No training
Internet use	0.185**	0.126***	0.181**	0.143***	0.273***	0.117***
	(0.079)	(0.044)	(0.072)	(0.037)	(0.068)	(0.039)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
N	302	1 147	302	1 147	302	1 147

Standard errors are shown in brackets. *** and ** are significant at 1 and 5% levels, respectively.

may be that the trained smallholder farmers can have higher agricultural production skills and obtain more information through Internet use, which promotes the adoption of agricultural production technology. This is consistent with the conclusion of Jia *et al*. (2013) who found that training could reduce farmers' fertilizer consumption to a certain extent.

Regarding the income level, smallholder farmers with less than the average income were grouped as low-income farmers, and the rest were grouped as high-income farmers. The marginal effects of Internet use for high-income farmers were significantly higher than that for the low-income group. This may be due to the fact that the high-income group can obtain more information about agricultural production technology through the Internet, and are more familiar with the risks and benefits of agricultural production technology; while high-income smallholder farmers have more capital to invest in agriculture and bear the risks of agricultural production technology.

4.3. Robustness test

This paper used endogenous switching model (ESM) method to address endogenous problem, and the results are shown in Table 8. The robustness of results showed that Internet use had a significant positive impact on agricultural production technology adoption. First, Internet use could significantly promote smallholder farmers' adoption of new crop varieties by 27.6% (ATT is 0.276, *t*-value is 16.08). Second, Internet use could significantly promote the adoption of water-saving irrigation technology by 38.4% (ATT is 0.384, *t*-value is 20.17). Third, Internet use could significantly promote the adoption of straw-returning technology by 9.4% (ATT is 0.094, *t*-value is 5.40). These results combine to show that Internet use had different effects on the adoption of technologies by smallholder farmers. Specifically, Internet use had a greater effect on the adoption of new crop varieties (27.6%) and water-saving irrigation technologies (38.4%) than on the adoption of straw-returning technology (9.4%).

5. Conclusion and policy recommendations

5.1. Conclusion

Using data of 1 449 farmers from 14 provinces/autonomous regions collected by National Agricultural and Rural Development Research Institute of China Agricultural University, from January to February 2019, and employing probit model, IV-probit model and PSM method, this paper explored the impact of Internet use on smallholder farmers' adoption of agricultural production technologies. The results showed that Internet use could significantly promote the adoption of agricultural production technologies by smallholder farmers, increasing the probability of adopting new crop varieties, water-saving irrigation technology and straw-returning technology by 0.200, 0.157 and 0.155, respectively. Heterogeneity analysis showed that the impact of Internet use on smallholder farmers' technology adoption had a greater impact on the farmers with low education level, training experience and high income. After addressing the self-selection and endogenous problems of Internet use, the conclusion was still robust. This study nevertheless has some limitations. First, surveyed households were not randomly selected and were more based on the social relationship of the investigators rather than the strict random sampling approach; Second, there were more students participating in the survey in some provinces

Table 7 Heterogeneity analysis on farmers' income levels

	New crop varieties		Water-saving irrigation technologies		Straw-returning technology	
	High income	Low income	High income	Low income	High income	Low income
Internet use	0.230***	0.141***	0.153***	0.141***	0.163***	0.110**
	(0.057)	(0.051)	(0.044)	(0.046)	(0.046)	(0.048)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
N	508	941	508	941	508	941

Standard errors are shown in brackets. *** and ** are significant at 1 and 5% levels, respectively.

Table 8 The average treatment effect of the impact of Internet use on the adoption of agricultural production technologies

	Samples	ATT[1)]	Standard deviation	*t*-value
New crop varieties	210	0.276***	0.249	16.08
Water-saving irrigation technology	210	0.384***	0.276	20.17
Straw-returning technology	210	0.094***	0.252	5.40

[1)] ATT, average treatment effect on the treated.
***, significant at 1% level.

than in other provinces, which may also lead to more samples being recovered in certain provinces. Third, the usage of dichotomous dependent variables may not be optimal, missing some important variations such as the degree and time of technology adoption.

5.2. Policy recommendations

This paper puts forward three policy recommendations. First, it is necessary to strengthen the construction of rural Internet infrastructure. At present, the infrastructure has not fully met the Internet use needs of smallholder farmers, primarily because of the problems of high network cost and slow network speed in many rural areas. It is in urgent need to strengthen the construction of agricultural information, disseminate the information to villages and households, and encourage the digital transformation of agricultural production. Second, it is important to provide training to smallholder farmers, assisting them in acquiring or improving Internet use skills. By December 2018, there were 222 million Internet users in rural areas of China, accounting for 26.7% of total Chinese internet users, and a 12.91 million increase from 2017. The rural Internet popularization rate was 38.4% in 2018, 0.3 percentage point higher than that at the end of 2017 (China Internet Network Information Center 2019). More attention should be paid to the training of Internet use skills for smallholder farmers. Taking into account the awareness and acceptance of smallholder farmers, the training content and training methods about smallholder farmers should be different from those for large-scale farmers. Finally, policy formulation should take into consideration the heterogeneity of smallholder farmers. The effectiveness of Internet use varies significantly by characteristics of farmer individuals and households. Therefore, the government should formulate targeted policies according to the needs of different smallholder farmers and provide tailored agricultural production methods to farmers of different knowledge, skill and income levels.

Acknowledgements

This work was supported by the Agricultural Science and Technology Innovation Program of Chinese Academy of Agricultural Sciences (CAAS-ASTIP-IAED-2020-06; CAAS-ASTIP-IAED-2021-SR-02; CAAS-ASTIP-IAED-2021-06).

Declaration of competing interest

The authors declare that they have no conflict of interest.

References

Abdulai A, Huffman W. 2014. The adoption and impact of soil and water conservation technology: Anendogenous switching regression application. *Land Economics*, **90**, 26–43.

Aker J C. 2010. Information from markets near and far: Mobile phones and agricultural markets in Niger. *American Economic Journal* (Applied Economics), **2**, 46–59.

Aker J C, Ksoll C. 2016. Can mobile phones improve agricultural outcomes? Evidence from a randomized experiment in Niger. *Food Policy*, **60**, 44–51.

Asfaw S, Shiferaw B, Simtowe F. 2010. Does technology adoption promote commercialization? Evidence from chickpea technologies in Ethiopia. In: *Centre for the Study of African Economies (CSAE) Conference on Economic Development in Africa*. University of Oxford, UK.

Asfaw S, Shiferawb B, Simtowec F, Lippera L. 2012. Impact of modern agricultural technologies on smallholder welfare: Evidence from Tanzania and Ethiopia. *Food Policy*, **37**, 283–295.

Boz I. 2016. Effects of environmentally friendly agricultural land protection programs: Evidence from the Lake Seyfe area of Turkey. *Journal of Integrative Agriculture*, **15**, 1903–1914.

Carter M R, Laajaj R, Yang D. 2016. Savings, subsidies, and technology adoption: Field experimental evidence from Mozambique. NBER Working Paper.

China Internet Network Information Center. 2019. *The 43rd Statistical Reports on Internet Development in China*. Beijing, China. (in Chinese)

Donovan K. 2017. *Anytime, Anywhere: Mobile Devices and Services and their Impact on Agriculture and Rural Development*. The World Bank Report. pp. 49–70.

Gao Y Y, Zang L Z, Sun J. 2018. Does computer penetration increase farmers' income? An empirical study from China. *Telecommunications Policy*, **42**, 345–346.

Genius M, Pantzios C J, Tzouvelekas V. 2006. Information acquisition and adoption of organic farming practices. *Journal of Agricultural and Resource Economics*, **31**, 93–113.

Gong X, Zhang J, Zhang H, Cheng M, Yu N. 2020. Internet use encourages pro-environmental behavior: Evidence from China. *Journal of Cleaner Production*, **256**, 1–11.

He Y, Wu S. 2019. Connection is empowerment: Practice and thinking on the connection between small farmers and modern agriculture. *China Rural Economy*, **6**, 28–37. (in Chinese)

Hu L, Zhang X, Zhou Y. 2019. Farm size and fertilizer sustainable use: An empirical study in Jiangsu, China. *Journal of Integrative Agriculture*, **18**, 2898–2909.

Hojo M. 2002. Farmer education and technology adoption: The choice of education measures. In: *Fall Meeting of the Japan Economic Association at Hiroshima University*. Niigata, Japan. pp. 13–14.

Issahaku G, Abdul-Rahaman A. 2019. Sustainable land management practices, off-farm work participation and vulnerability among farmers in Ghana: Is there a nexus?. *International Soil and Water Conservation Research*, **1**, 18–26.

Jack B K. 2013. Market inefficiencies and the adoption of agricultural technologies in developing countries. Center for International Development (CID) Working Papers.

Jia X, Huang J, Xiang C, Bergmann H, Zhang F. 2013. Farmer's adoption of improved nitrogen management strategies in maize production in China: An experimental knowledge training. *Journal of Integrative Agriculture*, **12**, 364–373.

Kislev Y, Schori-Bachrach N. 1973. The process of an innovation cycle. *American Journal of Agricultural Economics*, **55**, 28–37.

Leng C, Ma W, Tang J, Zhu Z. 2020. ICT adoption and income diversification among rural households in China. *Applied Economics*, **10**, 1–15.

Ma W. 2020. Heterogeneous effects of Internet use and adoption of sustainable production practices on rural incomes: Evidence from China. Australian Agricultural and Resource Economics Society (AARES) Annual Conference. Lincoln University, New Zealand.

Ma W, Abdulai A, Goetz R. 2018. Agricultural cooperatives and investment in organic soil amendments and chemical fertilizer in China. *American Journal of Agricultural Economics*, **100**, 502–520.

Ma W, Zhu Z. 2020. Internet use and willingness to participate in garbage classification: An investigation of Chinese residents. *Applied Economics Letters*, **10**, 1–6.

Muzari W, Gatsi W, Muvhunzi S. 2012. The impacts of technology adoption on smallholder agricultural productivity in sub-Saharan Africa: A review. *Journal of Sustainable Development*, **5**, 69–77.

Nie P, Ma W, Sousa-Poza A. 2020. The relationship between smartphone use and subjective well-being in rural China. *Electronic Commerce Research*, **10**, 1–27.

Peng D, Li Y, Li C. 2019. Research on the impact of Internet use on environmental protection attitude and environmental literacy. *Financial Science*, **8**, 97–109. (in Chinese)

Qiu H G, Wang X B, Zhang C P, Xu Z G. 2016. Farmers' seed choice behaviors under asymmetrical information: Evidence from maize farming in China. *Journal of Integrative Agriculture*, **15**, 1915–1923.

Schultz T W. 1964. *Transforming Traditional Agriculture*. The University of Chicago Press, Chicago and London. pp. 130–143.

Tadesse G, Bahiigwa G. 2015. Mobile phones and farmers' marketing decisions in Ethiopia. *World Development*, ***68***, 296–307.

Tatlıdil F F, Boz İ, Tatlidil H. 2009. Farmers' perception of sustainable agriculture and its determinants: A case study in Kahramanmaras province of Turkey. *Environment, Development and Sustainability*, **11**, 1091–1106.

Wossen T, Abdoulaye T, Alene A, Haile M G, Feleke S, Olanrewaju A, Manyong V. 2017. Impacts of extension access and cooperative membership on technology adoption and household welfare. *Journal of Rural Studies*, **54**, 223–233.

Wossen T, Alene A, Abdoulaye T, Feleke S Manyong V. 2019. Agricultural technology adoption and household welfare: Measurement and evidence. *Food Policy*, **87**, 1–9.

Wossen T, Berger T, Di Falco S. 2015. Social capital, risk preference and adoption of improved farm land management practices in Ethiopia. *Agricultural Economics*, **46**, 81–97.

Xin R, Chen K, Xiang Z. 2019. Factors affecting the adoption of on-farm milk safety measures in Northern China — An examination from the perspective of farm size and production type. *Journal of Integrative Agriculture*, **18**, 471–481.

Ye J, Zhang M. 2020. Modern agricultural development with small farmers as the main body: Theoretical turn, practical exploration and path construction. *Agricultural Economic Issues*, **1**, 48–58. (in Chinese)

Yoav K, Shchori-Bachrach N. 1973. The process of an innovation cycle. *American Journal of Agricultural Economics*, **55**, 28–37.

Executive Editor-in-Chief HUANG Ji-kun
Managing Editor WENG Ling-yun