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Impacts of internet access and use on grain productivity: evidence from Central China

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The impacts of Internet use on farming productivity in China have been extensively examined. However, existing studies focus on non-grain crops and often do not distinguish between Internet access and Internet use. This study investigates the effects of both Internet access and Internet use for farming purposes on farmers' technical efficiency (TE) using data collected from 855 grain-farmers in Central China. The TE is evaluated following a stochastic frontier analysis approach. Endogenous switching regression models are used to address the potential endogeneity issue associated with Internet access or use. Our empirical results show that the use of the Internet for obtaining farming-related information is crucial for improving farmers' TE. Having access to the Internet itself does not necessarily improve TE. This is also true when considering the effects through the two channels of technology adoption and risk management. Furthermore, using the Internet for non-farming purposes could impede the improvement of TE. Heterogeneity analysis indicates that the Internet can help to reduce the discrepancy of TE among grain farmers.

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Introduction

China feeds 20% of the world's population with 7% of its arable land, but it uses one third of the world's fertilizer and half of the world's pesticides (Ji et al., 2023). Thus, increasing farming efficiency is a major aim of China's agricultural development. Digitalization is an important approach to increasing the efficiency of food production while ensuring a sustainable agricultural system implemented in China (Shen et al., 2022; Walter et al., 2017). A fundamental digital technology, the Internet has been increasingly adopted in rural China in the past few years (Xiong and Li, 2020). The Internet penetration rate in China's rural areas was 55.9% in 2020, increasing 24.3% compared to 2015, and more than 99% of administrative villages nationwide have access to optical fiber and 4 G networks by 2021 (CNNIC, 2021).

The impacts of Internet access and use on farmers' agricultural productivity have been intensively investigated in recent years. Enormous studies have shown that the rapid development of the Internet in rural areas is an important driving force for improving agricultural production efficiency. For example, Lio and Liu (2006) estimated the agricultural production function using the data of 81 countries from 1995 to 2000 and found that the Internet had a significant positive impact on agricultural productivity. Li and Li (2020) pointed out that the prevalence of the Internet boosted the growth of agricultural total factor productivity at the provincial level. Much evidence at the farm level was also found in developing countries. Internet access helped improve the production efficiency of maize and rice growers in Bangladesh (Das et al., 2016), rice growers in Vietnam (Kaila and Tarp, 2019), and banana growers (Zheng et al., 2021) in China. Internet use helped improve the production efficiency of apple growers in China (Zhu et al., 2021).

Farmers' Internet use shapes agricultural productivity in various ways. First, it expands farmers' information channels and reduces the cost of acquiring information (Yang et al., 2023). For example, farmers can obtain market information about farming inputs readily from the Internet and purchase them online with reduced transaction costs (Deichmann et al., 2016; Reddy, 2018; Wu et al., 2020; Zanello et al., 2014). Existing studies have demonstrated that the use of Internet has improved smallholder farmers' access to markets and increased their returns from selling their products (e.g., Reddy and Mehjabeen, 2019). Farmers thus can choose pertinent and high-quality fertilizers or pesticides to improve their use efficiency (Weng et al., 2023; Zhu et al., 2021). Second, the Internet enables new ways for agricultural extension and helps improve farmers' adoption of new technologies (Aker and Ksoll, 2016; Norton and Alwang, 2020; Wycikhuis et al., 2018; Zheng et al., 2022). For example, Internet-facilitated extension services help farmers to adopt green technologies that increase the efficiency of fertilizer and water use (Ma & Wang, 2020). Third, the Internet can provide farmers with daily weather information including rainfall and temperature, as well as disaster information including hail and insect infestation.

This enables farmers to prepare for risks in advance and improve their ability to cope with risks (Barham et al., 2015; Wijayaratra and Dixit, 2016). Fig. 1 presents a framework consisting of three channels through which Internet use leads to an increase in farming efficiency.

Most existing studies, except Zhu et al. (2021), employ Internet access as an indicator of farmers' behavior in using the Internet (e.g., Fu and Zhu, 2023; Zheng et al., 2021). Internet access could be an adequate proxy for whether a farmer uses the Internet or not, but it does not necessarily indicate whether a farmer uses the Internet for farming-related purposes. It is commonly observed that farmers watch funny videos or play games on their smartphones in rural China. Using the Internet for entertainment and using it for obtaining agricultural information have different impacts on farming productivity. As long as the Internet is used in a way that improves farming practice, it can help improve farmers' technical efficiency.

In addition, existing studies mainly focus on high-value crops including fruits and vegetables (Zhu et al., 2021; Zheng et al., 2021). How farmers' use of the Internet influences the productivity of grain farming remains largely unknown. In the context of China, the farming of major grains is largely not market-oriented as they are purchased by the government at protective prices (Qian et al., 2020). In addition, Grain farming generally has such a low technological requirement that grain farmers heavily rely on their previous experience for choosing technologies (Fu and Zhu, 2023). As a result, grain farmers are generally less active in using the Internet to improve their farming than high-value crop farmers. Considering grains are farmed by most farmers not only in China but also in the developing world, our findings provide a more representative reflection of the impact of Internet use on farming than those based on high-value crop farming.

This study investigates the impacts of Internet access and Internet use on TE of grain production using data from 855 farm households in Central China (Henan, Hubei, and Hunan provinces). It provides evidence for grain farming (the majority of crop farming), whereas the existing few studies focus on fruit and vegetable farming. It also enriches literature that distinguishes the impacts of Internet access and Internet use on farming productivity. The rest of the paper is structured as follows. Section "Methods and data" presents the empirical models and data used in this study. Section "Results and discussion" reports the empirical results and discussions. Section 4 concludes and provides policy implications.

Methods and data

Measurement of technical efficiency. Stochastic frontier analysis (SFA) has been widely used to calculate the TE of grain production at the farm level (Latruffe et al., 2004; Cullinane et al., 2006). We choose the trans-log production function rather than the Cobb-Douglas function in analyzing input factor substitution.

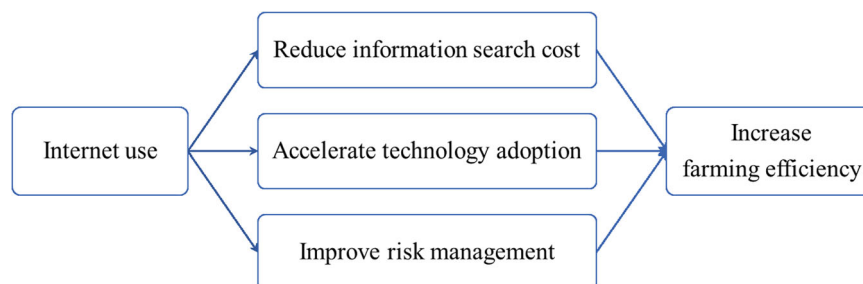


Fig. 1 Channels through which Internet use affects farming efficiency.

Table 1 The definition and descriptive statistics of variables.

The variable name	Measurement or unit	Mean	SD
Grain output	Total value of grain production (yuan/mu ^a)	1056.635	426.121
Labor	Number of family labors (hours/mu)	30.328	44.423
Fertilizer	Expenditures on fertilizers (yuan/mu)	101.148	166.329
Seeds	Expenditures on seedlings (yuan/mu)	93.731	86.615
Pesticide	Expenditures on pesticides (yuan/mu)	69.142	84.142
Other inputs	Expenditures on pesticides (yuan/mu)	152.164	122.939
Internet access	1 if the farmer has access to the Internet, 0 otherwise	0.685	0.464
Internet use	1 if the farmer uses the Internet to obtain farming-related information, 0 otherwise	0.274	0.446
Preference for ICT products	1 if the farmer owned a smartphone or computer in 2013 or before, 0 otherwise	0.249	0.433
Years of using the Internet	Years of access to the Internet (years)	2.975	3.443
Age	Age of household head (years)	56.350	9.561
Health	On a scale of 5, 1 = unhealthy and 5 = very healthy	3.724	1.092
Village cadre	1 if the household head is a village cadre, 0 otherwise	0.271	0.445
Education	0 = elementary school and below; 1 = a junior high school; 2 = high school or technical secondary school; 3 = College degree or above	0.719	0.725
Household size	Number of members residing in a household(persons)	4.415	2.010
Number of land parcels	The number of land parcels reflects the degree of fragmentation of cultivated land	6.273	6.700
The proportion of grain crops	The proportion of rice, maize, and wheat acreage to total acreage	0.841	0.238
Bus access	1 if there is a bus to the county in the village, 0 otherwise	0.458	0.499
Irrigation	1 if there is a shortage of irrigation water in the village, 0 otherwise	0.401	0.490
Henan Province	1 if the farmer is located in Henan province, 0 otherwise	0.296	0.457
Hubei Province	1 if the farmer is located in Hubei province, 0 otherwise	0.365	0.482
Hunan Province	1 if the farmer is located in Hunan province, 0 otherwise	0.339	0.474

^a1 hectare = 15 mu.

This choice is supported by the likelihood ratio test (the value is 26.02 and significant at the 1% level, as shown in Table A1 in the appendix). The function has the following form:

$$\ln(Y_i) = \beta_0 + \sum_{k=1}^5 \beta_k \ln(X_{ik}) + \frac{1}{2} \sum_{k=1}^5 \beta_{kk} \ln(X_{ik})^2 + \sum_{j=1}^5 \sum_{k=1}^5 \beta_{jk} \ln(X_{ij}) \ln(X_{ik}) + v_i - u_i \tag{1}$$

where the subscript *i* denotes the *i*th farm household, the subscripts *k*, and *j* both are factor indices, *Y_i* denotes the output of household *i*, *X_{ik}* or *X_{ij}* denotes the input of factor *k* or *j* of household *i*, *v_i* denotes the random error term, and *u_i* denotes the non-negative random variable related to technical invalidity. The TE of grain production is calculated as the aggregate TE of the production of rice wheat and maize, the three major staple crops in the studied regions (Zhang et al., 2019). Such an aggregate grain production efficiency is used primarily because farmers typically consider the inputs and outputs of the farming of all crops as a whole, rather than individually. For example, it is not possible to decompose some inputs according to individual crops, especially in the case of rotation (e.g., wheat and maize rotation). In addition, when using Internet for farming purposes, farmers generally do not distinguish crop types.

The subscripts *k* = 1, 2, 3, 4, 5, and *j* = 1, 2, 3, 4, 5, denoting five inputs, including labor, fertilizer, seedings, pesticide, and other inputs (mainly machinery and irrigation), as presented in Table 1. The value of *u_i* is obtained by estimating the above function. The value is then used to calculate the TE, which is calculated using the following formula:

$$TE = e^{-u_i} \tag{2}$$

Econometric strategy. In this study, we use endogenous switching regression (ESR) models to investigate the impacts of Internet access and Internet use on TE. This type of model is employed to address endogeneity issues in our analysis. Although

the two-stage least square method and the propensity score matching(PSM) method are also widely used to address endogeneity issues, they are not feasible for this study. The two-stage least square method deals with continuous endogenous explanatory variables, not the discrete ones in our study. The PSM method deals with the endogeneity issues caused by observable factors, but the endogeneity in our paper is mainly caused by unobservable factors.

The endogeneity issue due to circular causality may arise as farmers with higher TE are more likely to have access to the Internet or use it for farming purposes (Yan and Zheng, 2021). Farm households’ decisions on the access and use of the Internet are based on their cost-benefit analysis (Ma et al., 2020). Self-selection bias thus can occur in our analyses if households’ characteristics relevant to their decisions are not taken into account (Hou et al., 2018). The ESR model can solve endogeneity problems caused by unobservable variables when estimating the impact of a binary endogenous variable on outcome variables of interest, giving it an advantage over methods that can only solve endogeneity problems caused by observable variables, such as propensity score matching method and inverse probability weighted regression.

The estimation of ESR models is implemented in two stages. In the first stage, the Internet access or use decision variable *IU* is estimated using a model as follows:

$$\begin{aligned} IU_i^* &= \gamma_i Z_i + \mu_i \\ IU_i &= 1(IU_i^* > 0) \end{aligned} \tag{3}$$

where *IU_i^{*}* denotes the potential utility of Internet access or use decisions, and households make decisions based on expected income. If households’ expected income *IU_i^{*}* is greater than 0, then *IU_i* = 1, otherwise *IU_i* = 0. *Z* denotes the observable vectors including household characters and crop planting characters.

In the second stage, the determination equation of TE is established to estimate the efficiency difference caused by

accessing or using the Internet and not accessing or not using the Internet:

$$TE_{1i} = \alpha_{1i}X_{1i} + \sigma_{1u}\lambda_{1i} + \varepsilon_{1i} \text{ if } IU_i = 1 \quad (4a)$$

$$TE_{0i} = \alpha_{0i}X_{0i} + \sigma_{0u}\lambda_{0i} + \varepsilon_{0i} \text{ if } IU_i = 0 \quad (4b)$$

where TE_1 and TE_0 denote the TE of grain production of farmers who access or use the Internet and those who do not, respectively. Vector X is the control variable, but is different from vector Z in Eq. (3): at least one variable in vector Z is not in vector X . These variables affect the Internet use decisions of farmers but do not directly affect the TE of grain production. λ is the inverse Miles ratio calculated by Eq. (3); $\sigma_{1u} = cov(\varepsilon_1, u)$, $\sigma_{0u} = cov(\varepsilon_0, u)$, if σ_{1u} and σ_{0u} are statistically significant, then it indicates that the use of the Internet by farmers has an impact on the TE, and it is necessary for selective correction.

Based on ESR models (4a) and (4b), the average TE of farmers accessing or using the Internet and those not accessing or not using the Internet can be expressed as Eqs. (5) and (6). Their counterfactual TE is the average TE of farmers who access or use the Internet if they do not access or not use the Internet, and the average TE of farmers who do not access or not use the Internet if they do access or use the Internet, which can be expressed as Eqs. (7) and (8).

$$E(TE_{1i}|IU_i = 1) = \alpha_{1i}X_{1i} + \sigma_{1u}\lambda_{1i} \quad (5)$$

$$E(TE_{0i}|IU_i = 0) = \alpha_{0i}X_{0i} + \sigma_{0u}\lambda_{0i} \quad (6)$$

$$E(TE_{0i}|IU_i = 1) = \alpha_{0i}X_{1i} + \sigma_{0u}\lambda_{1i} \quad (7)$$

$$E(TE_{1i}|IU_i = 0) = \alpha_{1i}X_{0i} + \sigma_{1u}\lambda_{0i} \quad (8)$$

The average treatment effect on the treated (ATT) can be expressed by the following formula:

$$ATT = E(TE_{1i}|IU_i = 1) - E(TE_{0i}|IU_i = 1) \quad (9)$$

The average treatment effect on the untreated (ATU) can be expressed by the following formula:

$$ATU = E(TE_{1i}|IU_i = 0) - E(TE_{0i}|IU_i = 0) \quad (10)$$

Data and variables

Data collection. The data used for the analysis were collected from farmers in central China, specifically Hubei, Hunan, and Henan provinces in July 2019. These three provinces are important regions producing grains including rice, wheat, and maize in China, whose grain output accounts for 18.77% of the national total grain production in 2020. We employed a strategy combining stratified sampling and random sampling. A total of 108 villages and 1080 households were selected in the three studied provinces. To begin, counties in each province were divided into six groups based on population and farmland. Then, three towns were chosen at random from each sample county, two villages were chosen at random from each sample town, and ten farm households were chosen at random from each sample village. The data of 855 grain farmers have been used for the analyses.

Variables and descriptive analysis. The key explanatory variables in our empirical analyses are *Internet access* and *Internet use*. Farm households gain access to the Internet through broadband, WiFi, or mobile data. The variable “Internet access” is a dummy variable, whose value is 1 if farmers have access to the Internet via one of the three methods and 0 otherwise.

Internet use is indicated by the variable *whether to use the Internet to obtain farming-related information* in our study. This variable is made up of three indicators: “whether to learn

agricultural environmental information via the Internet,” “whether to search agricultural product purchase and sales information via the Internet,” and “whether to buy agricultural materials via the Internet.” The variable “Internet use” equals 1 if a farmer conducts any one of the three activities listed above and 0 otherwise.

The key to estimating the ESR model using the two-stage method is to choose appropriate exclusive variables. In other words, at least one variable in the vector Z of the Internet access or use decision equation is not included in the TE decision equation. These variables are also known as instrumental variables (IVs) (Song et al., 2018). The IVs, in our case, should directly affect farmers’ decisions on Internet use but do not directly affect the TE of grain production (Shiferaw et al., 2014). Following Chen (2013), we adopt farmers’ “preference for ICT products” as the IV of *Internet access* and adopt “years of using the Internet” as the IV of *Internet use*. Preference for ICT products has a direct impact on Internet use and fits the correlation requirements of instrumental variables and endogenous explanatory factors. Acceptance, purchasing intent, and use frequency of these new products will be influenced by the preference for ICT products (Donat et al., 2009; Verdegem and Verhoest, 2009). People who have stronger preferences for ICT products are more likely to purchase ICT products including smartphones and computers early, and thus intend to use the Internet more in various ways, e.g., sending and receiving emails, talking, and playing games. Meanwhile, the preference for ICT products is not necessarily related to agricultural production behavior. The preference for ICT products, therefore, can be a satisfactory instrumental variable for Internet access. A person’s historic preference for ICT products has nothing to do with their current agriculture activities (Chen, 2013). Similarly, people who have used the Internet for a longer period are more adept at using it and thus more likely to obtain agricultural-related information via the Internet. Years of using the Internet can be thought of as a valid IV of Internet use because it is based on a consumption decision made years ago and thus has no direct impact on current agricultural production behavior.

In this paper, the preference for ICT products is measured by “whether households owned smartphones or computers in 2013 or before”. This is primarily due to a series of measures implemented by Internet service providers to tap the rural Internet consumption market, which resulted in a much higher growth rate of Internet users in rural areas than in urban areas of China in 2013. Therefore, whether the household owned smartphones or computers in 2013 or before indicates that farmers prefer smartphones and computers over purchasing smartphones or computers to improve the TE of grain production.

In addition, the demographical characteristics of the household head, characteristics of the household, crop farming, and villages are controlled in our models (Zhu et al., 2021; Zheng et al., 2021). Province dummy variables are introduced to control the regional fixation effect. Table 1 presents the definitions and descriptive statistics of all variables used in our models.

Results and discussion

Technical efficiency scores. The TE scores of each input and their interactions are calculated using the data of 855 grain farmers in the studied regions. The results are presented in Table A1 in the Appendix.

Table 2 presents the TE values of farmers with and without access to the Internet. The results show that the average TE of 855 grain farmers is 0.734, with values ranging from 0.255 to 0.933. In particular, the mean value for 586 grain farmers with Internet

Table 2 TE of farmers accessing to the Internet or not.

Sample group	Number of observations	Mean	Standard Deviation	Min.	Max.
Access to Internet	586	0.744	0.117	0.302	0.933
Not having access to the Internet	269	0.713	0.135	0.255	0.920
All	855	0.734	0.123	0.255	0.933

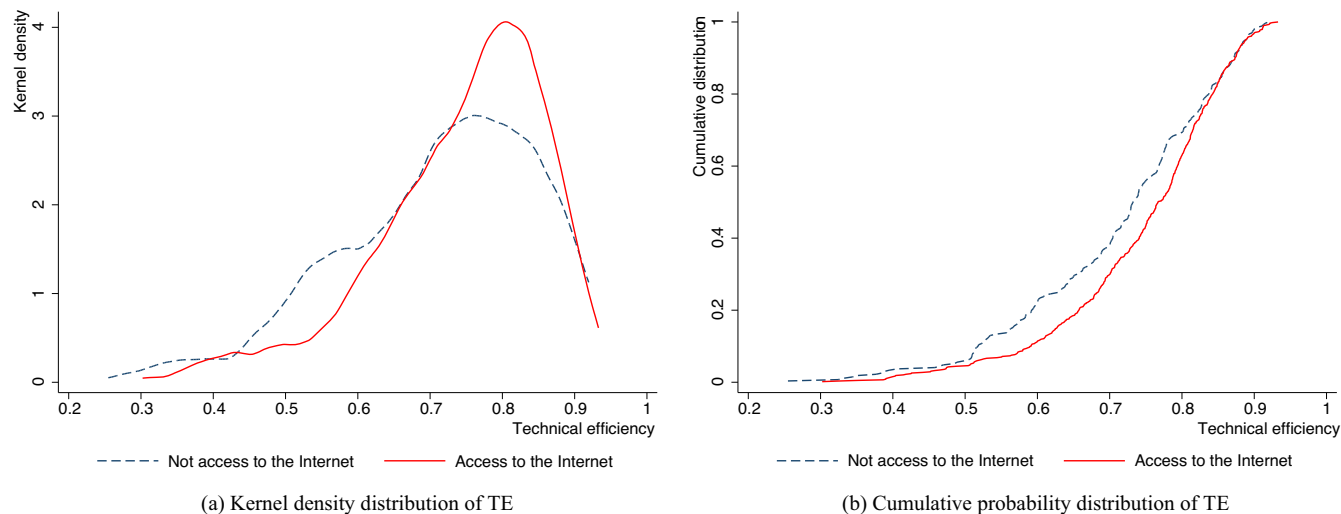


Fig. 2 Distribution of TE of farmers accessing the Internet or not. a Kernel density distribution of TE. **b** Cumulative probability distribution of TE.

access is 0.744, which is 4.35% higher than the value for those without Internet access (269 grain farmers). Our *t*-test of difference in means shows that the TE of farmers with Internet access is 0.031, significantly larger than that of farmers without Internet access. This suggests that having access to the Internet could help grain farmers improve their TE.

Figure 2 depicts the kernel density distribution (left panel) and cumulative probability distribution (right panel) of TE for grain farmers who have and do not have Internet access. The distribution of TE for grain farmers with Internet access is much more centralized than for those without Internet access, with most values concentrated around 0.8. Furthermore, grain farmers with Internet access have much higher TE than grain farmers without Internet access in the high TE zone, whereas grain farmers with Internet access have lower TE than grain farmers without Internet access in the low TE zone. The right panel shows that the cumulative distribution gap between grain farmers with and without Internet access widens around 0.65 and narrows around 0.83. The cumulative distribution curve of grain farmers with Internet access catches up to the cumulative distribution curve of grain farmers without Internet access when the TE value reaches around 0.85. This means that among grain farmers with Internet access, the proportion of grain farmers in the high TE zone (0.65–0.85) is higher than among grain farmers without Internet access. These graphs show that the TE of grain farmers with Internet access is significantly higher than that of grain farmers without Internet access in general. The results and conclusions need to be further empirically tested.

Estimation results of ESR models. This section presents results obtained by estimating our ESR models. The results are presented in Table 3. Since the validation of IVs is key to estimating these models, we performed the falsification test for our two IVs, “preference for ICT products” for Internet access and “years of using the Internet” for Internet use, before the estimation (Ma et

al., 2021). The falsification test shows that two IVs are significantly associated with Internet access and Internet use but are not significantly associated with farmers’ TE. The results of running two-stage least square regressions (2SLS) with the IVs show that both Cragg-Donald Wald F statistics are greater than the critical value of 10% for the Stock-Yogo weak recognition test (shown in Table A2), indicating our two IVs are both valid. According to the results in Table 3, we are also able to find that the coefficients of influence of both IVs are significant at the 1% level. In addition, provinces dummy variables are added to the model to control the differences between provinces.

Factors affecting internet access and internet use. Results of the first-stage estimation of the ESR models show determinants of a household’s Internet access and Internet use. As presented in columns (1) and (4) of Table 3, the impact of the household heads’ age, health status, family size, village cadre experience, and education on Internet access and Internet use is straightforward. In particular, with a significance level of 10%, the proportion of grain crops, a variable representing grain production specialization, has a negative impact on using the Internet to obtain agricultural information. This could be because grain farmers are already very skilled in the production process and methods of the three major grain crops, but lack experience in the production of non-major grain crops, necessitating the acquisition of new product knowledge. They can learn through the use of the Internet.

Factors affecting TE of grain production. Results of the second-stage estimation of the ESR models provide information about the factors affecting TE in various conditions of Internet access and Internet use. Column (2) and (3) of Table 3 shows the factors that affect the TE of farmers with and without access to the Internet, respectively. TE of farmers with access to the Internet is positively influenced by household heads’ age and bus access, whereas negatively influenced by household size and household heads’

Table 3 Estimated results of the ESR model.

Variables	(1) Internet access	(2) TE Internet access =1	(3) TE Internet access =0	(4) Internet use	(5) TE Internet use=1	(6) TE Internet use=0
Age	-0.048*** (0.005)	0.005*** (0.001)	<0.000 (0.002)	-0.040*** (0.006)	0.005*** (0.001)	0.001 (0.001)
Household size	0.076*** (0.022)	-0.005* (0.003)	0.002 (0.004)	-0.019 (0.025)	0.002 (0.005)	0.004* (0.002)
Health	0.009 (0.041)	0.006 (0.005)	0.020*** (0.007)	0.130*** (0.049)	-0.016* (0.009)	0.014*** (0.004)
Village cadres	0.191* (0.100)	-0.006 (0.012)	0.011 (0.019)	0.281** (0.110)	-0.019 (0.020)	0.008 (0.011)
Education	0.298*** (0.068)	-0.024*** (0.007)	0.001 (0.016)	0.325*** (0.071)	-0.057*** (0.013)	0.004 (0.008)
Number of land parcels	-0.004 (0.006)	<0.001 (0.001)	-0.002 (0.001)	0.009 (0.007)	-0.002 (0.001)	<0.000 (0.001)
Proportion of grain crops	-0.220 (0.182)	0.042* (0.021)	0.048 (0.033)	-0.376* (0.204)	0.098*** (0.037)	0.041** (0.020)
Irrigation	-0.066 (0.087)	0.005 (0.010)	0.010 (0.015)	-0.132 (0.100)	0.026 (0.018)	0.002 (0.009)
Bus access	-0.136 (0.087)	0.027*** (0.010)	0.068*** (0.015)	-0.046 (0.097)	0.039** (0.017)	0.047*** (0.009)
Preference for ICT products	0.266*** (0.095)					
Years of using the Internet				0.046*** (0.012)		
Province	Yes	Yes	Yes	Yes	Yes	Yes
Observations	855	586	269	855	234	621
Constant	2.760*** (0.386)	0.553*** (0.044)	0.640*** (0.142)	1.051** (0.432)	0.718*** (0.076)	0.590*** (0.050)
$\rho1/\rho0$		-0.983*** (0.008)	-0.115 (0.401)		-0.982*** (0.008)	-0.222 (0.192)
LR test of Indep. Eqns.		60.31***		47.05***		

*, **, and *** indicate significance at the 10%, 5%, and 1% significance levels, respectively. Standard errors are in parentheses.

Table 4 The average treatment effects of Internet access on TE.

Sample group	with Internet Access	without Internet access	ATT	ATU
with Internet access	0.740	0.713	0.027***	
without Internet access	0.961	0.713		0.248***

Authors' calculation. ***denotes significance at the 1% level.

education. TE of farmers without access to the Internet is positively influenced by household heads' health status and bus access.

Results in columns (5) and (6) of Table 3 show the factors influencing TE for the subsample of farmers using and not using the Internet to obtain agricultural information, respectively. These results are similar to those for the subsample of farmers with and without Internet access. The only difference is that household heads' health has a negative impact on TE for farmers using the Internet to obtain agricultural information. This is possible as those farmers have the motivation to use their knowledge in farming practice but there is a time lag for the influence to be observed.

Average treatment effects analysis. Using the results of running the ESR models, we analyze the impacts on expected TE of three circumstances: Internet access, Internet access excluding using the Internet for agricultural information, and Internet use for agricultural information.

Impacts of Internet access. We first examine the expected TE of grain farmers with and without Internet access under actual and counterfactual conditions. Setting the value of the Internet variable to be 1 if farmers have Internet access and 0 otherwise, we calculate ATT and ATU using the ESR model results. As presented in Table 4, ATT and ATU are 0.027 and 0.248, respectively. They are both significant at the 1% significance level. The results indicate the TE of grain farmers who have Internet access would reduce if they did not have Internet access, whereas grain farmers who do not currently have Internet access would be more efficient if they did. These results indicate that Internet access can improve farmers' TE of grain production.

Impacts of Internet access without use for agricultural information. To control the influence of Internet use, we further calculate the ATT and ATU derived from the subsample excluding farmers who use the Internet for agricultural information. Excluding such

Table 5 Average treatment effects of Internet access only on TE.

Sample group	Access to Internet	Not having access to the Internet	ATT	ATU
Farmers who have access to the Internet but do not use it	0.740	1.000	-0.260***	
Farmers without Internet access	1.000	0.713		0.287***

Authors' calculation. ***denotes significance at the 1% level.

farmers from the original entire sample, we obtained a subsample of 634 grain farmers. Setting the value of the Internet variable to be 0, if farmers do not access the Internet; setting the value of the Internet variable to be 1 if farmers access the Internet but do not use it to obtain agricultural information. In a counterfactual framework, we continue to use the ESR model to calculate ATT and ATU. The preference for ICT products is also an IV. As presented in Table 5, the ATT is -0.260 and the ATU is 0.287, indicating that Internet access impedes the improvement of TE for grain farmers who currently have access to the Internet but do not use it to obtain agricultural information. These results suggest that having access to the Internet itself does not necessarily improve TE. Considering the findings in the previous section, it is likely that using the Internet for agricultural purposes is the key driver for TE improvement.

Impacts of Internet use. Furthermore, we delve into the impact of Internet use for agricultural purposes. As presented in Table 6, ATT and ATU are 0.042 and 0.271, respectively, indicating that Internet use currently improves the TE of grain production. If grain farmers do not use the Internet, the TE will reduce by 0.042, which is double that in the case of simply having access to the Internet (0.027, as shown in Table 4). According to the ATU estimation results, TE will increase by 0.271 for farmers who do not use the Internet to obtain agricultural information if they do. This value is also greater than the corresponding one in the case of simply having access to the Internet. Together, these results confirm that using the Internet for agricultural purposes is key to the improvement of TE for grain farmers.

Heterogeneity analysis. The strength of the Internet's impact on the TE of grain production may vary based on the realized TE of grain production. We use an unconditional quantile regression (UQR) to examine the potential heterogeneous effects of Internet access and Internet use, and a two-stage control function approach to address the potential endogeneity issue of Internet access and Internet use (Zheng et al., 2021).

The IVs used in our analyses are identical to those mentioned previously. Table 7 presents the estimated results at the 25th, 50th, and 75th quantiles. We find that Internet access and use have the greatest impact on TE of grain production at the 25th quantile and have no effect at the 50th and 75th quantiles. These findings suggest that the Internet can help to reduce the discrepancy of TE among grain farmers.

Mechanism analysis. This section analyses the mechanisms through which Internet access and use affect farmers' TE. Here we focus on technology adoption and risk management, the two channels discussed in the Introduction section. Existing studies have provided strong evidence for the positive impacts of farmers' adoption of new technologies and risk management on their TE (DeLay et al., 2022; Zheng et al., 2018). This study will test the impacts of Internet access and use on the two channels. ATT and ATU are calculated using the ESR method. In the regressions, farmers' access to and use of the Internet are used as the core explanatory variables, and farmers' behaviors of adopting new technologies and purchasing agricultural

Table 6 Average treatment effects of Using the Internet for agricultural information on TE.

Sample group	Use the Internet	Not using the Internet	ATT	ATU
Internet user	0.747	0.704	0.042***	
Internet non-user	1.000	0.729		0.271***

Authors' calculation. ***denotes significance at the 1% level.

insurance are the key explained variables for the two channels, respectively. Farmers' behavior of adopting new technologies is indicated by the number of new technologies that they adopt, whereas their behavior of purchasing agricultural insurance is indicated by whether they purchased agricultural insurance or not. Because the purchase of agricultural insurance is a binary variable, we use the endogenous switching probit model in the corresponding regression. Table 8 displays the results of ATT and ATU calculated using the ESR method.

Our results show the impact of Internet access on farmers' adoption of new technologies is negative for ATT and positive for ATU, indicating that farmers' Internet access cannot currently promote their adoption of new technologies. In addition, the results show the impact of Internet use on farmers' adoption is positive for both ATT and ATU, indicating that farmers' use of the Internet to acquire agricultural production information can promote their adoption of new technologies. The impacts of Internet access and use have the same pattern for the channel of agricultural insurance purchase. These findings reveal that only by using the Internet for agricultural information can farmers' adopt new technologies and risk management, simply having access to the Internet does not necessarily lead to such improvement.

Conclusions and policy implications

The impacts of Internet use on agricultural production or productivity have been extensively documented. However, existing studies mainly focus on the farming of high-value crops, leaving the impacts on grain farming, the majority of crop farming remains unknown. In addition, most existing studies simply represent Internet use by the access to the Internet, which ignores the difference of using the Internet for different purposes. This study aims to fill these gaps by investigating the effects of both Internet access and Internet use for farming purposes on farmers' TE using data collected from 855 grain-farmers in Central China.

The TE is evaluated following a stochastic frontier analysis approach. The potential endogeneity issue associated with Internet access or use is addressed using endogenous switching regression models. Average treatment effects analysis based on regression results indicates that having access to the Internet itself does not necessarily improve farmers' TE if the Internet is not used for obtaining information highly related to farming. This is also true when considering the effects through the two channels of technology adoption and risk management. Using the Internet for

Table 7 Heterogeneity analysis: UQR model estimation.

Variables	Selected quantiles			25th	50th	75th
	25th	50th	75th			
Internet access	0.1221** (0.070)	0.073 (0.050)	-0.015 (0.042)			
Internet use				0.153* (0.082)	0.071 (0.058)	0.049 (0.049)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Observations	855	855	855	855	855	855

* and ** indicate significance at the 10% and 5% significance levels, respectively. Standard errors are in parentheses.

Table 8 The impact of the Internet on farmers adopting new technologies and purchasing agricultural insurance.

	Adopt new technology		Purchase agricultural insurance	
	ATT	ATU	ATT	ATU
Internet access	-0.043***	0.040***	-0.149***	0.309***
Internet use	0.055***	0.197***	0.239***	0.369***

Note: Authors' calculation. *** denotes significance at the 1% level.

non-farming purposes, e.g., entertainment can impede the improvement of TE. Whether the Internet is used for farming-related purposes is crucial for improving TE. Heterogeneity analysis indicates that the Internet can help to reduce the discrepancy of TE among grain farmers. Our study emphasizes the importance of delving into specific usage when examining the influence of the Internet on agricultural productivity. Although there may be a concern that we did not distinguish crop types in the evaluation of TE, it is not likely to overturn the core findings of our study.

Our findings have at least two policy implications. One is that efforts should be made to encourage and guide rural Internet users to use the Internet for farming-related purposes. Without such guidance, farmers are often likely to use the Internet more for entertainment, which does not help improve farming productivity. The other is that efforts should be made to enrich Internet products (e.g., smartphone APPs) providing agricultural information or services. Such products can be provided by both the public and private sectors.

Data availability

The datasets analyzed during the current study are available from the corresponding author upon reasonable request. The data are not publicly available due to privacy and ethical restrictions.

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Author contributions

XL and HX conceptualized the study, obtained the data, conducted the data analysis and drafted the paper. JH contributed to the model development and results interpretation. GL contributed to the formation and compilation of conclusion. All authors read and approved the final manuscript.

Competing interests

The authors declare no competing interests.

Ethical approval

This article does not contain any studies with human participants performed by any of the authors.

Informed consent

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Additional information

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