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Internet Use, Sustainable Agricultural Practices and Rural Incomes: Evidence from China*

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Relatively little is known about the association between Internet use and environmentally-friendly agricultural innovation adoption. To fill this void, this study examines the impact of Internet use on the adoption of sustainable agricultural practices (SAPs) and their heterogeneous effects on farm income and household income. Unlike previous studies that analyse the dichotomous decision of agricultural innovation adoption, this study captures the number of SAPs adopted. We apply both endogenous-treatment Poisson regression model and unconditional quantile regression model to analyse unique farm-level data collected from China. The empirical results show that Internet use exerts a positive and statistically significant impact on the number of SAPs adopted, and the joint effects of Internet use and SAP adoption on farm income and household income are heterogeneous. In particular, we show that Internet use has a larger impact at the upper tail of household income but it has no significant impact on farm income. SAP adoption is negatively associated with farm income and household income across the selected quantiles.

Key words: Internet use, Sustainable agricultural practices, Impact evaluation, Unconditional quantile regression, Rural incomes, China.

1. Introduction

Several studies have shown that agricultural production has brought a range of issues such as water and air pollution, land degradation, loss of biodiversity and increased human health risks, which poses challenges to land productivity, food safety and security, and environmental and health concerns (e.g. Atreya *et al*. 2012; Alavaisha *et al*. 2019; Midingoyi *et al*. 2019; Wilson and Tisdell 2001). To maintain or enhance agricultural production performance, adoption of sustainable agriculture can play a role because it moves agricultural production towards a system that is more sustainable.

The FAO (1989) argues that sustainable agriculture is characterised with conserving resources, environmentally non-degrading, technically

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appropriate, economically and socially acceptable. Following these attributes, sustainable agricultural practices (SAPs) have been broadly defined in the literature. Different terminologies of SAPs have been used by scholars, including such as conservation tillage, legume intercropping, crop rotation, uses of improved varieties, the application of farmyard manure and organic fertiliser, adoption of soil and water conservation technology, conservation agriculture technology and integrated pest management (IPM) technology (e.g. Adolwa *et al*. 2019; Kassie *et al*. 2013; Ma and Abdulai 2019; Midingoyi *et al*. 2019; Ndiritu *et al*. 2014; Rodriguez *et al*. 2009; Tambo and Mockshell 2018; Teklewold *et al*. 2013; Wossen *et al*. 2015; Zeweld *et al*. 2017).

A growing number of studies have investigated the effects of SAPs, and they have reached the consensus that SAP adoption enables to improve both farm economic and environmental performance (e.g. Farquharson *et al*. 2008; Kassie *et al*. 2010; Teklewold *et al*. 2013; Abdulai and Huffman 2014; Wossen *et al*. 2015; Manda *et al*. 2016; Midingoyi *et al*. 2019). For example, Abdulai and Huffman (2014) show that the adoption of water and conservation technologies increases rice yields and net returns in the Northern region of Ghana. Manda *et al*. (2016) show that adoption of SAPs (crop rotation, improved varieties and residual retention) increases both maize yields and household income in rural Zambia. Midingoyi *et al*. (2019) find that the adoption of IPM technologies significantly increases mango yields and net income but reduces insecticide use in Kenya, contributing to an improvement of environment and human health. In their investigation on Ghana and Kenya, Adolwa *et al*. (2019) reveal that adoption of interpreted soil fertility management leads to an increase in maize yields.

Despite the multiple benefits associated with the SAP adoption, the adoption rate of SAPs is still low in rural areas of developing countries (Adolwa *et al*. 2019; Midingoyi *et al*. 2019). A better understanding of constraints and incentives that determine farmers' adoption behaviour for SAPs is, therefore, of importance for designing agri-environmental policies that could stimulate their SAP adoption and enhance farm economic performance.

Previous studies investigating the determinants of SAP adoption have mainly focused on household and plot-level characteristics, without taking into account the role of information and communication technologies (ICTs) (e.g. D'souza *et al*. 1993; Rodriguez *et al*. 2009; Kassie *et al*. 2009, 2013, 2015; Ndiritu *et al*. 2014; Manda *et al*. 2016). Information asymmetry and the existence of insufficient information access lead to higher information search costs, which affect farmers' incentives to adopt innovative agricultural technologies. Access to ICTs enables to reduce information asymmetry and improve production (Brown and Roper 2017; Kiiza and Pederson 2012; Ogutu *et al*. 2014; Salim *et al*. 2016; Ma *et al*. 2018b). For example, Kiiza and Pederson (2012) show that access to ICT-based market information is crucial to the adoption of seed technologies for maize, beans and groundnut and to improve smallholder farmer yields and income. Ogutu *et al*. (2014) show that ICT-based market information services increase the use of modern varieties and fertilisers, land and labour productivity in Kenya. However, to the best of our knowledge, no previous studies have investigated whether information access through modern technologies has an impact on SAP adoption in China.

In this study, we contribute to the literature on sustainable agriculture by exploring the association between Internet use, adoption of SAPs and rural incomes from four aspects. First, unlike previous studies that have considered the role of ICTs such as smartphones and computers (Hou *et al*. 2019; Kiiza and Pederson 2012; Liu *et al*. 2020; Ma *et al*. 2018b), we consider Internet use through access to broadband Internet services. This is because that Internet accessibility enables to support more ICTs devices such as smartphones, computers, tablets and TVs, and it allows all household members to enjoy the benefits associated with Internet use at the same time. Second, we analyse the impact of Internet use on the intensity of SAP adoption, with a focus on the number of SAPs adopted. Very few studies have investigated the intensity of SAP adoption. A notable exception is a study by Arslan *et al*. (2014) who has defined the intensity of adoption as the proportion of total cultivated land that is under a given practice. However, this study did not consider the role of Internet use in SAP adoption.

Third, we employ an endogenous-treatment Poisson regression model to correct for selection bias associated with voluntary Internet use, by taking into account both observed and unobserved heterogeneities. Previous studies have used either a propensity score matching technique or an inverse-probability weighted regression adjusted estimator to estimate the effects of a binary treatment variable (e.g. Adolwa *et al*. 2019; Fentie and Beyene 2019; Hou *et al*. 2019; Manda *et al*. 2018; Tambo and Mockshell 2018). However, the two approaches fail to address the selection bias arising from unobserved factors. Fourth, we examine the heterogeneous effects of Internet use and SAP adoption on farm income and household income by estimating an unconditional quantile regression model. Prior studies have examined the impact of Internet use on rural household welfare (Chang and Just 2009; Khanal *et al*. 2015; Ma *et al*. 2020a) or the impact of SAP adoption on farm economic performance (Kassie *et al*. 2013; Manda *et al*. 2016). However, given the possible interdependence between Internet use and SAP adoption, their effects on rural incomes should be modelled jointly.

The remainder of this paper is organised as follows: the next section provides estimation strategies. Section 3 presents data and descriptive statistics. The empirical results are presented and discussed in Section 4. The last section concludes and proposes policy implications.

2. Estimation strategies

2.1 Selection bias issue and model selection

The decision to use the Internet is not random but voluntarily selected by farm households (Chang and Just 2009; Khanal *et al*. 2015; Ma *et al*. 2020a).

Farmers who use the Internet (i.e. treated group) may have systematically different characteristics from those who do not use the Internet (i.e. control group). Under the existence of such self-selection issue, estimating the impact of Internet use on SAP adoption, a count variable that measures the number of SAPs adopted, using a Poisson regression approach would produce biased estimates.

Previous studies investigating the effects of information technology adoption or policy programme intervention have used a propensity score matching (PSM) method (e.g. Fentie and Beyene 2019; Hou *et al*. 2019) and an inverse-probability weighted regression adjusted (IPWRA) estimator (Manda *et al*. 2018; Adolwa *et al*. 2019; Tambo and Mockshell 2018). For example, using the PSM approach, Fentie and Beyene (2019) have analysed the impact of row planting technology on the welfare of rural households in Ethiopia. Using the IPWRA estimator, Tambo and Mockshell (2018) have examined the drivers and welfare impacts of individual and combined implementation of three conservation agriculture components (i.e. minimum soil disturbance, residual retention and crop rotation) in nine sub-Saharan African countries. A strong assumption associated with the PSM approach is that if the treatment model (e.g. the Internet use model in our case) is correctly specified, the estimates of the treatment effects will be consistent and unbiased. However, in the presence of misspecification in the outcome model, the estimated results are still biased. Compared with the PSM approach, the IPWRA estimator provides more reliable results because, in essence, it has a doubly robust property. The doubly robust property of the IPWRA estimator assumes that the estimates of the treatment effects are consistent and unbiased once the outcome regression model or the treatment regression model is correctly specified (Soczyński and Wooldridge 2017). Both PSM and IPWRA approaches mitigate selection bias issue based on observed heterogeneities. However, when unobserved factors (e.g. farmers' innate abilities and motivations) affect farmers' decisions to use the Internet and to adopt SAPs simultaneously, the estimated results from PSM and IPWRA would be biased.

In this study, we employ an endogenous-treatment Poisson regression (ETPR) model to estimate the impact of Internet use on a Poisson distributed count (i.e. SAP adoption) (Stata 2019). The ETPR model addresses the selection bias originating from both observable and unobservable factors (Bratti and Miranda, 2011; Stata 2019). In addition, the ETPR model can help estimate the treatment effects of Internet use on SAP adoption.

2.2 The ETPR model

The ETPR model is a two-stage estimation approach. The first-stage models a household's decision to use the Internet. Following previous studies on Internet access and ICT use (Chang and Just 2009; Ma *et al*. 2020a), farm households' decision to use the Internet is modelled in a random utility framework. Let T_i^* denote the utility difference between using the Internet (U_{iU}) and the utility from not using the Internet (U_{iN}), such that a household i will choose to use the Internet if $T_i^* = U_{iU} - U_{iN} > 0$. However, the two utilities are subjective and cannot be observed. Alternatively, they can be expressed as a function of observable components in a latent variable model as follows:

$$T_i^* = \alpha_i Z_i + \mu_i \text{ with } T_i = \begin{cases} 1 & \text{if } T_i^* > 0 \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

where T_i^* is a latent variable which represents the probability of Internet use, and it is determined by the observed variable T_i that indicates the actual status of Internet use, that is $T_i = 1$ if a household i uses the Internet and $T_i = 0$ otherwise; Z_i is a vector of variables that represent household and farm-level characteristics (e.g. age, gender, household size and farm size); α_i is a vector of parameters to be estimated; and μ_i is a random error term.

Information access through Internet use enables rural farmers to identify and process the information on the sustainable agricultural technologies, through the mechanism of their awareness of the benefits associated with new technologies (Islam et al. 2019; Kiiza and Pederson 2012; Ogutu *et al.* 2014). This is rational, given the fact that the markets for innovative technologies are not perfect. A recent study by Islam et al. (2019) also shows that the more accuracy and reliability of information transmission about the quality of technology circulated, the higher probability farmers adopt it. Therefore, in the second-stage estimation of the ETPR model, we identify the impact of Internet use on SAP adoption. Assuming that SAP adoption is a linear function of a dummy variable for Internet use and a vector of other explanatory variables,X_i, the SAP adoption function can then be expressed as follows:

$$A_i = \beta_i T_i + \gamma_i X_i + \varepsilon_i \tag{2}$$

where A_i is the SAP adoption variable, which represents the number of SAPs adopted; T_i refers to Internet use variable, which is defined above; β_i and γ_i are vectors of parameters to be estimated; ε_i is an error term. The impact of Internet use on the intensity of SAP adopted is measured by the parameter γ_i. For the purpose of model identification, at least one instrumental variable (IV) should be included in Z_i in Equation (1)but it does not appear in X_i in Equation (2). The IV is valid if it affects farmers' Internet use decision but does not directly affect farmers' SAP adoption decisions. In this study, a social network variable that measures whether a household's neighbour purchases goods online is used as an IV. Due to peer effects, neighbour's Internet use behaviour may affect a household's decision to use the Internet, but it does not directly affect a household's SAP adoption decision. A

Pearson correlation analysis is used to test the validity of the IV (see Table A1 in the Appendix S1).

The coefficients estimations of the variables in the ETPR model only provide partial information about the association between Internet use and SAP adoption. In view of this, we follow Stata (2019) and calculate the average treatment effects (ATE) and the average treatment effects on the treated (ATT) to provide a better understanding about the impact of Internet use on SAP adoption as follows:

$$ATE = E(Y_{Ii} - Y_{0i}) = E\{E(Y_{Ii} - Y_{0i}|Z_i)\} \quad (3)$$

$$ATT = E(Y_{Ii} - Y_{0i}|T_i = 1) = E\{E(Y_{Ii} - Y_{0i}|Z_i, T_i = 1)|T_i = 1\} \quad (4)$$

where the Equation (3) is estimated using the full samples that include both Internet users and non-users, while the Equation (4) is estimated only using the samples of the treated group (i.e. Internet users) in a counterfactual context.

2.3 Heterogeneous effects of Internet use and SAP adoption on income

Previous studies have separately analysed the impact of Internet use and SAP adoption on farm economic performance and rural household welfare (e.g. Chang and Just 2009; Khanal *et al*. 2015; Manda *et al*. 2016; Ma *et al*. 2018; Tambo and Mockshell 2018). For example, Ma *et al*. (2018b) show that Internet use through smartphones significantly increases farm income, off-farm income and household income in rural China. Midingoyi *et al*. (2019) find that adoption of SAPs in terms of IPM practices exerts a positive and statistically significant impact on crop yields and net income for mango farmers in Kenya.

In this study, we not only capture the interaction of the two household activities on rural incomes but also have interests in understanding how Internet use and SAP adoption affect the distributions of farm income and household income. Therefore, a quantile regression model analysis is considered. Previous studies have revealed that the conditional quantile regression model estimation is greatly relying on the employed covariates, and it is impossible to freely alter the control variables without redefining the quantiles (Borah and Basu 2013; Firpo *et al*. 2009; Mishra *et al*. 2015; Ma *et al*. 2020a). Therefore, we estimate an unconditional quantile regression (UQR) model to capture the heterogeneous effects of Internet use and SAP adoption on farm income and household income.

Following Firpo *et al*. (2009), a UQR model can be estimated as a simple OLS regression on a transformed dependent variable using the recentered influence function (RIF). Specifically, the following equation can be estimated:

$$RIF(Y_i; Q_\tau, F_Y) = \eta_i T_i' + \lambda_i A_i' + \xi_i X_i + \varphi_i \tag{5}$$

where Y_i refers to an outcome variable (i.e. either farm income or household income); Q_τ denotes the τ-th quantile of the outcome's cumulative distribution F_Y; T_i' and A_i' represent predicted Internet use variable and predicted SAP adoption variable, respectively. Instead of using the original variables, the predicted variables enable to address the endogeneity of the Internet use and SAP adoption variables (Chang and Mishra 2012). X_i is a vector of explanatory variables; η_i, λ_i and ξ_i are parameters to be estimated; and φ_i is an error term that captures unobserved heterogeneities. In particular, the RIF in Equation (5) is defined as:

$$RIF(Y_i; Q_\tau, F_Y) = Q_\tau + \frac{\tau - I(Y_i \leq Q_\tau)}{f_Y(Q_\tau)} \tag{6}$$

where the probability distribution function of variable Y_i is f_Y, and $I(Y_i \leq Q_\tau)$ is a dummy variable which indicates whether the outcome variable (i.e. farm income or household income) is below Q_τ.

3. Data and descriptive statistics

3.1 Data collection

The data used in this study were collected from a farm household survey that was conducted in January 2019. A multistage sampling procedure was used for data collection. First, three provinces (Sichuan, Henan and Fujian) were randomly selected, respectively, from western, central and eastern regions of China. The three provinces are different in terms of economic and geographic conditions. For example, the GDPs per capita in Sichuan, Henan and Fujian are 48,883, 50,152 and 91,197 Yuan in 2018, respectively (NBSC 2019). Sichuan consists of two geographically distinct regions, with fertile basin in the eastern region and numerous mountains in the west of the province. Fujian is mostly mountainous, while Henan has a diverse landscape with floodplains in the east and mountains in the west. Second, two cities from each province were randomly selected. These include Chengdu and Meishan in Sichuan, Sanmenxia and Hebi in Henan and Fuzhou and Ningde in Fujian. Third, two towns within each city and then three villages in each town were randomly selected. Finally, we randomly selected and interviewed between 15 and 25 households in each village. This procedure results in a total of 598 samples, including 413 Internet users and 185 non-users.

A structured questionnaire was developed and used for data collection. The collected information refers to the year 2018. The questionnaire designed several blocks of questions including household and farm-level characteristics (e.g. age, education, farm size and family size), Internet use status, sustainable agricultural practices adopted, environmental perception, distance to input market and asset ownership, etc.

3.2 Measurement of key variables

The primary objectives of this study are to analyse the impact of Internet use on SAP adoption and to assess the heterogeneous effects of Internet use and SAP adoption on farm income and household income. Both farm income per capita and household income per capita are collected. In particular, farm income refers to the revenue obtained from crop and livestock production. Household income is comprised of farm income, off-farm income and income received from other sources such as transfer and rents. Internet use is measured as a binary variable, which equals to one if a household has access to the broadband Internet, and zero otherwise. SAP adoption is measured as a count variable in this study. Following previous studies (e.g. Antle and Diagana 2003; D'souza *et al*. 1993; Kabir and Rainis 2014; Kassie *et al*. 2013; Manda *et al*. 2016) and considering agricultural production practice in China, we prepared a list of sustainable agricultural practices and asked farmers to select the practices they had adopted in 2018. The final list of practices includes 10 practices, including (1) soil testing; (2) organic fertiliser; (3) farmyard manure; (4) pollution-free pesticide; (5) water-saving irrigation technology; (6) deep ploughing; (7) crop residue retention; (8) film harmless treatment; (9) adoption of modern varieties; and (10) IPM technology. A value of one is given if a given technology was adopted and zero otherwise. The values [0, 10] were then used to measure the intensity of SAPs adopted.

3.3 Descriptive statistics

Table 1 presents the descriptive statistics of SAPs adopted by households. It shows that farmyard manure and organic fertiliser are the most frequently adopted sustainable agricultural technologies among survey farmers. In particular, 52.3% and 36.5% of farm households in our sample have adopted farmyard manure and organic fertiliser, respectively. Soil testing and film harmless treatment are the two technologies which rarely adopted by smallholder farmers. The survey shows that only around 5% of households have adopted soil testing and formula fertilisation technology, and less than 4% of them have treated agricultural films in a harmless way. Around 8% of farmers have adopted water-saving technologies, and 10.5% of them have adopted IPM technology for pest control.

Figure 1 demonstrates the distribution of the number of SAPs adopted by farm households. The figure shows that around 30% of households did not adopt any SAPs. Among the sample households who adopted SAPs, the majority of farm households (i.e. 22.24%) adopted two SAPs. This is followed by the number of households who adopted only one SAP, which

Table 1 Definition and descriptive statistics of 10 SAPs adopted by rural households

Types	Definition	Mean	Std. Dev.
Soil testing	1 if soil testing and formula fertilisation technology is used, 0 otherwise	0.049	0.215
Organic fertiliser	1 if organic fertiliser is applied, 0 otherwise	0.365	0.482
Farmyard manure	1 if farmyard manure is applied, 0 otherwise	0.523	0.500
Pollution-free pesticide	1 if pollution-free pesticide is applied, 0 otherwise	0.264	0.441
Water-saving irrigation technology	1 if water-saving irrigation technology is used, 0 otherwise	0.082	0.275
Deep ploughing	1 if deep ploughing technology is used, 0 otherwise	0.109	0.312
Crop residue retention	1 if straw mulching technology is used, 0 otherwise	0.176	0.381
Film harmless treatment	1 if agricultural film is collected for recycling after its usage rather than left it on the land, 0 otherwise	0.037	0.188
Modern varieties	1 if modern varieties is adopted, 0 otherwise	0.080	0.272
IPM technology	1 if integrated pest management (IPM) technology is adopted, 0 otherwise	0.105	0.307

accounts for 18.39% of the total samples. Only 1% of households adopt 8 or 9 SAPs. Among 10 questions on SAPs, Figure 1 shows that none of the households has adopted all SAPs.

In addition to the key variables defined above, we draw on the existing literature on Internet use and ICT adoption to select other exogenous explanatory variables (Deng *et al*. 2019; Goldfarb and Prince 2008; Khanal

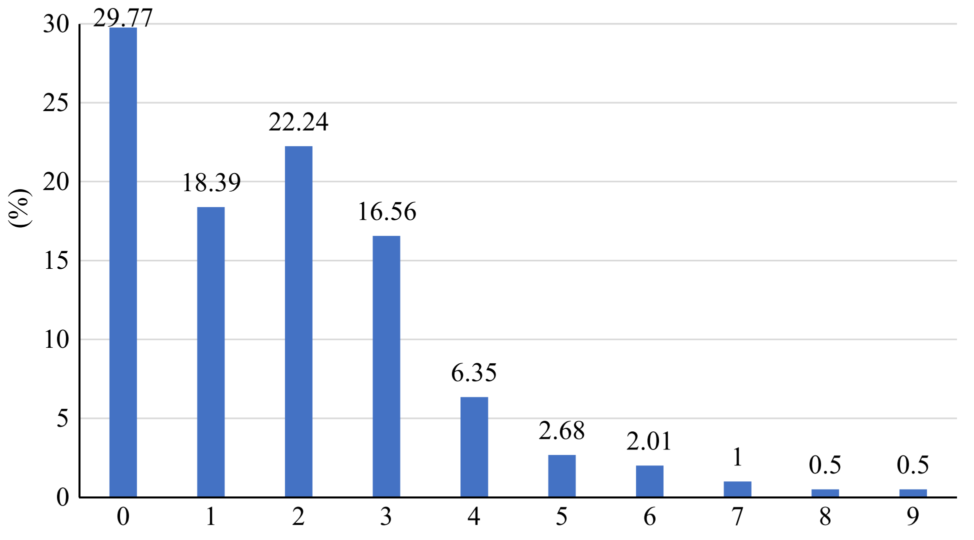

Figure 1 Sample distribution for the number of SAPs adopted.

et al. 2015; Leng *et al*. 2020; Ma *et al*. 2020a, 2020b; Martínez-Domínguez and Mora-Rivera, 2020; Mishra *et al*. 2009; Penard *et al*. 2015; Pénard *et al*. 2013; Salim *et al*. 2016). In particular, we include age, gender, education, family size, farm size, membership, remittance, asset ownership, environmental perception, logistic service, distance to market and the location variables as the control variables.

The existing literature justifies the inclusion of the control variables. Regarding personal characteristics of the household head, previous studies have found that Internet use is negatively associated with age (Khanal *et al*. 2015; Penard *et al*. 2015; Ma *et al*. 2020b) but positively related to educational attainment (Mishra *et al*. 2009; Pénard *et al*. 2013; Khanal *et al*. 2015; Deng *et al*. 2019). These studies also reported that male household heads are more likely to use the Internet than their female counterparts. We expect similar influence of these variables on the likelihood of Internet use in this study. Consistent with previous studies (Deng *et al*. 2019; Martínez-Domínguez and Mora-Rivera 2020), we expect a positive relationship between family size and Internet use. The impact of farm size on the Internet use does not reach consensus. For example, Ma *et al*. (2018b) showed that farm size has a positive and significant impact on Internet use via smartphones, while Leng *et al*. (2020) found that farm size negatively affects Internet use via ICTs such as computers and smartphones. Thus, we do not assign any a *priori* sign expectation for the farm size variable in our analysis.

In rural areas, agricultural cooperatives can provide their members with acquired production and marketing information (Liu *et al*. 2019; Zhang *et al*. 2019), and farmers with cooperative membership may choose not to use other channels for information acquisition. Thus, we expect membership in agricultural cooperatives negatively affects rural farmers' decision to use the Internet. Wealth is an essential determinant of Internet use (Deng *et al*. 2019; Martínez-Domínguez and Mora-Rivera 2020). Although remittance helps to relax credit constraints among rural households, farmers may use the remittance for basic living expenditures rather than purchase luxury Internet services. Thus, a negative relationship between remittance and Internet use is expected. Regarding physical assets, Martínez-Domínguez and Mora-Rivera (2020) have shown that ownership of computer and mobile phone has a direct relationship with the probability of Internet use. Similarly, we expect the ownership of the asset, exerts a positive effect on Internet use. Farmers who have concerned the association between agricultural production and environmental protection may use modern technologies such as computers and smartphones to search for more information on environmentally-friendly practices. Thus, we expect that farmers' environmental perception positively affects their Internet use.

The availability of logistic service can directly determine farmers' decision to use the Internet for online shopping. Ma *et al*. (2020b), in their study for China, have reported that rural farmers' decision to use the Internet is positively affected by logistic service. Thus, we also expect the availability of logistic service in the village is positively associated with Internet use. Consistent with previous studies (Khanal *et al*. 2015; Deng *et al*. 2019), we expect distance to market is negatively associated with Internet use. Finally, we incorporate a set of provincial dummy variables to control for unobserved region-specific characteristics such as socioeconomic conditions, institutional arrangements and differences in rural infrastructure development.

The definitions and descriptive statistics of the variables used for empirical analysis are presented in Table 2. The table shows that the average number of SAPs adopted by rural households is only 1.789 (out of 10), suggesting the low rate of SAP adoption. Thus, from the sustainability perspective of modern agricultural production, it is significant to promote and enhance the adoption of SAPs. Around 69% of rural households in the samples use the Internet. On average, farm income and household incomes are 4,536 yuan/capita and 20,270 yuan/capita, respectively. The average age of household heads is appropriately 50 years old, and around 71.6% of household heads in our sample are male. The average education level of household heads is 6.99 years. The average family size is 4.72 members, and the mean of farm size is 6.93 mu (1mu = 1/15 hectare).

Table 3 presents the mean differences in household and farm-level characteristics between Internet users and non-users. It shows that Internet users and non-users are systematically different in some observed characteristics. For example, referred to the household heads of Internet non-users, that of Internet users are younger and more likely to be better educated. The family size for Internet users is relatively larger than that for non-users. Internet users are less likely to have membership in agricultural cooperatives and to obtain remittance from household members, compared with their non-user counterparts. The information presented in the lower part of Table 3 shows that Internet users are more likely to adopt SAPs than non-users. Regarding income variables, Table 3 shows that there is no significant difference in both farm income and household income between Internet users and non-users. These findings appear to indicate that Internet use increases the probability of SAP adoption, and it does not have a statistically significant impact on farm income and household income. However, the information presented in Table 3 is inconclusive because the simple descriptive statistics do not account for various confounding factors (e.g. age, education, farm size, family size, farmers' motivations and innate abilities) that affect farmers' decision to use the Internet. Therefore, rigorous assessment of the effects of Internet use should rely on robust econometric approaches.

4. Empirical results

4.1 ETPR results

The estimates for the impact of Internet use on SAP adoption are presented in Table 4. The estimated correlation between the treatment-assignment error

Table 2 Definition and descriptive statistics of the variables

Variables	Definition	Mean	Std. Dev.
Dependent variables			
SAP adoption	The number of sustainable agricultural practices (SAPs) adopted by a household 2018 (0–10)	1.789	1.730
Internet use	1 if household used Internet in 2018, 0 otherwise	0.691	0.463
Farm income	Farm income (1,000 Yuan/capita)†	4.536	13.180
Household income	Household income (1,000 Yuan/capita)	20.270	32.800
Independent variables			
Age	Age of household head (years)	49.54	11.29
Gender	Gender of household head:1 = Male, 0 = Female	0.716	0.451
Education	The schooling years of household head (years)	6.990	3.472
Family size	Number of people residing in a household	4.717	1.628
Farm size	Total land cultivated in mu‡	6.930	9.118
Membership	1 if household is a member in agricultural cooperatives, 0 otherwise	0.125	0.331
Remittance	1 if household receives remittance, 0 otherwise	0.363	0.481
Asset ownership	1 if household owns a microwave oven, 0 otherwise	0.249	0.433
Environmental perception	Farmer's self-reported perception on the statement 'agricultural production should consider environment protection' (from 1 = strongly disagree to 5 = strongly agree)	4.013	0.858
Logistic service	1 if there is an e-commerce logistic service centre in the village, 0 otherwise	0.403	0.491
Distance to market	Distance to the nearest input market (km)	19.970	64.060
Fujian	1 if household resides in Fujian, 0 otherwise	0.227	0.420
Sichuan	1 if household resides in Sichuan, 0 otherwise	0.321	0.467
Henan	1 if household resides in Henan, 0 otherwise	0.452	0.498
Social network	1 if households' neighbour purchases items online, 0 otherwise	0.637	0.481

Note: †1 USD = 6.80 Yuan in 2019; ‡1 mu = 1/15 hectare.

and the outcome error $\rho_{\varepsilon\mu}$ is -0.948, and the statistic value is statistically significant at the 1% level. The findings indicate the presence of negative selection bias, that is there exist the same unobservable factors that positively affect the probability of Internet use but are negatively associated with the number of SAPs adopted. Therefore, the Poisson regression model, the PSM approach and IPWRA would underestimate the impact of Internet use on SAP adoption, and the ETPR model is more appropriate.

In the sections below, we firstly discuss the determinants of Internet use, followed by a discussion of the determinants of SAP adoption. Then, the treatment effects of Internet use on SAP adoption are presented and discussed.

4.1.1 Determinants of Internet use

Our results show that the decision of using the Internet or not is correlated with the characteristics of household and farm. The coefficient of the

Table 3 Mean differences of selected variables between Internet users and non-users

Variables	Internet users	Non-users	Mean Diff.
Age	47.94 (0.977)	53.11 (0.540)	–5.169*
Gender	0.730 (0.040)	0.690 (0.020)	0.035
Education	7.510 (0.300)	5.830 (0.170)	1.676*
Family size	4.850 (0.143)	4.420 (0.080)	0.436*
Farm size	6.680 (0.807)	7.480 (0.470)	–0.798
Membership	0.090 (0.029)	0.190 (0.010)	–0.100*
Remittance	0.340 (0.042)	0.420 (0.020)	–0.077*
Asset ownership	0.300 (0.038)	0.130 (0.020)	0.173*
Environmental perception	4.050 (0.076)	3.930 (0.040)	0.121
Logistic service	0.490 (0.042)	0.200 (0.020)	0.294*
Distance to market	17.49 (5.662)	25.49 (3.080)	–8.003
Fujian	0.230 (0.037)	0.230 (0.020)	0.001
Sichuan	0.310 (0.041)	0.340 (0.020)	–0.020
Henan	0.460 (0.044)	0.440 (0.020)	0.020
Social network	0.710 (0.020)	0.480 (0.040)	0.226*
SAP adoption	2.000 (0.151)	1.310 (0.090)	0.689*
Farm income	4.670 (1.167)	4.230 (0.750)	0.440
Household income	19.910 (2.904)	21.090 (1.110)	–1.180
Observations	413	185	598

Note: $^{*}P < 0.1$, $^{**}P < 0.05$, $^{***}P < 0.01$; Standard deviation in parentheses.

household head's age is negative and statistically significant, suggesting that older farmers are less likely to use the Internet. The findings in the literature are mixed. Our result is consistent with the findings of Goldfarb and Prince (2008) and Penard *et al*. (2015) who showed that young people are more likely to use the Internet because they are usually more technologically savvy. However, our finding contradicts with the result of Chang and Just (2009) who showed that Internet access is positively associated with the operator's age. Gender variable has a positive and statistically significant coefficient. The finding suggests that male heads are more likely to use the Internet. The existence of a digital divide between genders has also reported in other studies (CNNIC 2017; Goldfarb and Prince 2008; Poushter 2016). For example, CNNIC (2017) shows that the male-to-female ratio of Chinese Internet users is 52.4: 47.6. Consistent with the previous studies (Chang and Just 2009; Khanal *et al*. 2015), our result shows better-educated farmers are more likely to use the Internet. Better education increases farmers' ability to judge the usefulness of the Internet and enables them to acquire information related to farm and off-farm activities by using the Internet.

The positive and statistically significant coefficient of family size suggests that households with larger member size are more likely to use the Internet. To some extent, larger family size indicates more labour endowments and more off-farm labours, while the Internet enables to serve as a convenient tool for household members to communicate with each other or run farm and off-farm business smoothly. On the other hand, larger family size may also indicate a higher dependency ratio, while Internet use may facilitate such type

Table 4 Impact of Internet use on SAP adoption

Variables	ETPR model			Poisson regression model	
	Internet use (Coefficients)	SAP adoption (Coefficients)	SAP adoption (IRRs)	SAP adoption (Coefficients)	SAP adoption (IRRs)
Internet use		1.079 (0.154)*,†	2.941*,†	0.339 (0.085)*,†	1.404*,†
Age	–0.027 (0.008)*,†	0.006 (0.005)	1.006	–0.001 (0.004)	0.999
Gender	0.317 (0.137)*,†	–0.285 (0.085)*,†	0.752*,†	–0.218 (0.076)*,†	0.804*,†
Education	0.051 (0.021)*,†	0.016 (0.013)	1.016	0.029 (0.012)*,†	1.029*,†
Family size	0.116 (0.043)*,†	–0.012 (0.024)	0.988	0.014 (0.022)	1.014
Farm size	–0.010 (0.007)	0.004 (0.003)	1.004	0.001 (0.002)	1.001
Membership	–0.453 (0.167)*,†	0.292 (0.094)*,†	1.340*,†	0.183 (0.086)*,†	1.201*,†
Remittance	–0.161 (0.127)	0.223 (0.079)*,†	1.249*,†	0.191 (0.075)*,†	2.211*,†
Asset ownership	0.309 (0.156)*,†	0.065 (0.091)	1.067	0.120 (0.082)	1.127
Environmental perception	0.078 (0.065)	0.103 (0.046)*,†	1.109*,†	0.118 (0.045)*,†	1.125*,†
Logistic service	0.779 (0.129)*,†	–0.003 (0.084)	0.997	0.178 (0.073)*,†	1.195*,†
Distance to market	–0.002 (0.001)	–0.000 (0.001)	1.000	–0.000 (0.001)	1.000
Sichuan	0.257 (0.191)	1.230 (0.120)*,†	3.422*,†	1.284 (0.112)*,†	3.612*,†
Henan	–0.463 (0.186)*,†	0.925 (0.131)*,†	2.521*,†	0.815 (0.121)*,†	2.260*,†
Social network	0.318 (0.127)*,†				
Constant	0.271 (0.625)	–1.922 (0.377)*,†	–0.369*,†	–1.284 (0.325)*,†	0.277*,†
$\rho_{\mu\varepsilon}$	–0.948 (0.032)*,†				
Wald test (rho = 0)	$Chi^2(1) = 32.89$, Prob> $chi^2 = 0.000$				
Observations	598		598	598	598

Note: *Standard errors in parentheses; $p < 0.1$, $**p < 0.05$, $***p < 0.01$; The reference region is Fujian.

of family to access to information for better taking care of children and elders. Membership in an agricultural cooperative has a negative and statistically significant impact on Internet use. This finding may reflect the fact that one of the primary functions of the cooperative organisations is to explore information (e.g. production and marketing information) needed by smallholder farmers. Therefore, cooperative members are less likely to use the Internet for information acquisition. This finding is also observed by Penard *et al.* (2015), who showed that membership in a voluntary association is negatively related to the decision to use the Internet.

Asset ownership increases the probability of Internet use. To some extent, the asset is an indicator of household wealth, and thus, wealthy households are more likely to use the Internet. Internet use also varies with local economic conditions and geographic differences. We show that the presence of an e-commerce logistics service centre in the village is positively and significantly correlated with Internet use, a finding that is consistent with the finding of Ma *et al.* (2020b). Although Internet use has enabled rural households to purchase and sell online, the convenient and available logistic service is the base of e-commerce. Our results show that compared with farm households located in Fujian (reference group), those in Henan are less likely to use the Internet. Finally, the coefficient of the social network variable is positive and statistically significant, suggesting the presence of peer effects that affect farm households' decisions to use the Internet. The social network serves as an IV in the ETPR model; that is, we do not expect it has a statistically insignificant impact on SAP adoption.

4.1.2 Determinants of SAP adoption

The third column of Table 4 demonstrates the factors that affect the number of SAPs adopted. Because the interpretation of coefficients estimated from a count model regression is not straightforward, we calculate and present the incidence rate ratios (IRRs) in the fourth column of Table 4 to ease our interpretation. In particular, IRRs are obtained by exponentiating the count model regression coefficients, that is IRR = exp (coefficient) (Erdogdu 2013; Zhang *et al.* 2019).[1] For comparison, we also estimated the impact of Internet use on SAP adoption using a Poisson regression model and presented the coefficients and IRR results in the last two columns of Table 4.

Turning to the variable of interest, the IRR of Internet use variable in the ETRP model is positive and statistically significant. The finding suggests that on average, Internet users adopt 2.941 times more SAPs than non-users. Figure 1 shows that in our samples, more than half of the households (57.19%) only adopted either 1 or 2 or 3 SAP(s), while here we show the important role of Internet use in enhancing environmentally-friendly SAP adoption in rural areas. The potential mechanism is that Internet use helps

[1] The IRRs of the variables are estimated using the '*lincolm*' and '*eform*' STATA commands after estimating the ETPR model (Stata 2019).

reduce the information asymmetry associated with the adoption of sustainable agricultural technologies and facilitate farmers' understanding about the benefits associated with the technologies, which finally contributes to an increase in the adoption rate. The IRR results, estimated using the Poisson regression model (the last column of Table 4), show the Internet users adopt 1.404 times more SAPs than non-users. The IRR estimate of the traditional Poisson regression model is smaller than that estimated from the ETPR model. However, the finding that the Poisson regression model underestimates the SAP adoption impact of Internet use is not implausible because the approach fails to take into account the selection bias associated with the self-selection of Internet use. However, the results of ETRP model estimates reveal the presence of negative selection bias ($\rho_{\mu\varepsilon} = -0.948$).

Among other factors that affect the number of SAPs adopted, the gender variable has a negative and statistically significant coefficient. The IRR estimate shows that relative to female household heads, male household heads adopt 0.752 times more SAPs on average. Our finding suggests that Internet use enables to empower rural women to adopt agricultural innovations. The findings can be largely explained by the feminisation of China's agriculture, as well as in other developing countries (de Brauw *et al.* 2008; Mukhamedova and Wegerich 2018).

The positive and statistically significant coefficient of membership variable suggests that farmers with cooperative membership are more likely to adopt the SAPs. The findings are largely consistent with the findings in previous studies which show that cooperative membership has a positive and statistically significant impact on the probability of adopting organic soil amendments such organic manure and farmyard manure (Ma *et al*. 2018a). A positive and statistically significant IRR of remittance suggests that households receiving remittance from other household members adopt 1.249 times more SAPs, compared with their counterparts who did not receive any remittance. This is consistent with the finding of Williams et al. (2013) that there is a positive association between remittance and adoption of resource-conserving technologies in Nepal.

The coefficient of the variable representing environmental perception is positive and statistically significant, suggesting that farmers, who perceive that agricultural production should take into account its impact on the environmental performance, are more likely to adopt SAPs. The positive association between farmer's environmental perception and SAP adoption has also been reported in the literature. In their study on China, Ma and Abdulai (2019) show that farmers who are aware of the negative impacts of pesticide use on the environment are more likely to adopt IPM technology. We also find that SAP adoption is affected by location fixed effects. Relative to farmers accommodating in Fujian (reference province), those living in Sichuan adopts 3.422 times more SAPs and those living in Henan adopt 2.521 times more SAPs.

Table 5 Treatment effects of Internet use on SAP adoption

	ATE	z-value	ATT	z-value
ETPR model	1.703 (0.248)**	6.87	1.323 (0.132)**	10.03
PSM technique*,†	0.548 (0.170)**	3.22	0.574 (0.196)**	2.92
IPWRA estimator	0.309 (0.146)**	2.12	0.151 (0.158)	0.95

Note: $^{**}P < 0.05$ and $^{***}P < 0.01$; Standard errors are presented in parenthesis.
†Nearest neighbour matching technique is used.

4.1.3 Treatment effects of Internet use on SAP adoption

The results presented in Table 4 show the IRR of Internet use on the number of SAPs adopted from a marginal perspective. To provide a better understanding, we follow Stata (2019) and calculate the treatment effects (i.e. ATE and ATT) of Internet use on the number of SAPs adopted. The results are presented in Table 5.

The estimated ATE of Internet use on the number of SAPs adopted is 1.703, which is statistically significant at the 1% level.[2] The finding suggests that the average household will take 1.703 more SAPs when it uses the Internet. The estimated ATT of Internet use on the number of SAP adopted is 1.323, indicating that the average household in the treated group (i.e. Internet users) will take 1.323 more SAPs than it would if it did not use the Internet. Generally, our results support the conclusion that Internet use promotes SAP adoption in rural areas.

For the purpose of comparison, we also estimated the impact of Internet use on the number of SAP adopted using the PSM technique and IPWRA estimator and presented the results in the lower parts of Table 5. The results show that the estimated ATEs of Internet use on the number of SAPs adopted by PSM and IPWRA models are 0.548 and 0.309, respectively, while the estimated ATTs of Internet use on the number of SAPs adopted are 0.574 and 0.151, respectively. The findings confirm the positive role of Internet use in promoting SAP adoption in rural areas. However, the treatment effects estimated by the PSM and IPWRA approaches are smaller than that obtained from the ETRP approach. This is not implausible. As indicated earlier, PSM and IPWRA models fail to take into account unobserved selection bias, and we found a negative selection bias in the results of ETPR estimation. Thus, the analyses without considering the unobserved selection bias underestimate the impacts of Internet use on SAP.

4.2 UQR results

The UQR estimates for the joint effects of Internet use and SAP adoption on farm income and household income are presented in Table 6. As discussed

[2] The ATE and ATT estimates are different from IRR, so they cannot be interpreted straightforwardly.

Table 6 Impact of Internet use and SAP adoption on farm income and household income: UQR model estimates

	Farm income			Household income		
	25th	50th	75th	25th	50th	75th
Internet use (predicted)	0.431	–0.026	0.047	0.144	0.372**	0.417**
	(0.296)	(0.313)	(0.427)	(0.160)	(0.155)	(0.169)
SAP adoption (predicted)	–0.196**	–0.112	–0.235*	–0.089**	–0.123***	–0.170***
	(0.081)	(0.089)	(0.122)	(0.045)	(0.042)	(0.049)
Age	0.017*	0.005	0.006	0.012**	0.015***	0.013**
	(0.010)	(0.011)	(0.015)	(0.006)	(0.005)	(0.006)
Gender	–0.252*	–0.067	–0.013	–0.089	–0.206**	–0.265***
	(0.151)	(0.163)	(0.215)	(0.082)	(0.080)	(0.092)
Education	–0.007	0.028	0.002	0.014	–0.006	0.008
	(0.025)	(0.025)	(0.033)	(0.012)	(0.012)	(0.014)
Family size	–0.088**	–0.074*	–0.166***	–0.068***	–0.109***	–0.106***
	(0.044)	(0.044)	(0.060)	(0.023)	(0.022)	(0.024)
Farm size	0.031***	0.036***	0.069***	0.012***	0.016***	0.025***
	(0.006)	(0.007)	(0.010)	(0.003)	(0.002)	(0.003)
Membership	0.293	0.374*	0.933***	–0.055	0.164	0.178
	(0.200)	(0.212)	(0.312)	(0.109)	(0.102)	(0.109)
Remittance	0.016	–0.020	–0.082	0.152**	0.174***	0.218***
	(0.119)	(0.125)	(0.157)	(0.063)	(0.061)	(0.065)
Asset ownership	–0.103	–0.003	0.032	0.085	0.035	0.013
	(0.142)	(0.145)	(0.201)	(0.076)	(0.073)	(0.080)
Environmental perception	–0.073	0.005	–0.039	–0.019	–0.033	–0.003
	(0.059)	(0.066)	(0.087)	(0.034)	(0.031)	(0.034)
Logistic service	–0.124	0.020	–0.153	–0.038	–0.209*	–0.160
	(0.232)	(0.244)	(0.342)	(0.132)	(0.124)	(0.141)
Distance to market	0.001**	0.002***	0.001	0.000	0.000	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Henan	0.063	–0.354	–0.005	0.290**	0.201*	–0.093
	(0.214)	(0.224)	(0.304)	(0.117)	(0.109)	(0.121)
Constant	6.905***	7.486***	8.777***	8.928***	9.525***	9.809***
	(0.445)	(0.497)	(0.692)	(0.282)	(0.249)	(0.274)
Observations	598	598	598	598	598	598

Note: Standard errors in parentheses; ***$P < 0.01$, **$P < 0.05$, *$P < 0.1$.
The dependent variables refer to the log-transformed forms of per capita farm income and per capita household income, respectively.
Both Fujian and Sichuan variables were automatically dropped out in regressions due to the multicollinearity issue.

earlier, we use the predicted variables for the Internet use and SAP adoption to correct for the potential endogeneity issues of the two variables.[3] For the sake of simplicity, we only present and discuss the results estimated at the

[3] A seemingly unrelated regression (SUR) model is used to jointly estimate the Equations (1) and (2) for the purpose of predicting Internet use and SAP adoption variables. By estimating the SUR model, the Internet use variable was removed out in Equation (2) to avoid the autocorrelation issue of the predicted variables. The results are presented in Table A2 in the Appendix.

25th, 50th and 75th quantiles, respectively. Following Thornton and Innes (1989) and Mishra *et al.* (2015), the proportional impacts of the discrete variables (e.g. gender, membership, remittance, asset ownership and location dummies) on farm income and household income are measured as $p_i = [exp(\alpha_i) - 1]$, where α_i is the coefficient of the variable.

The UQR results in Table 6 show that Internet use and SAP adoption affect farm income and household income heterogeneously and statistically differently. Such heterogeneous findings could not be observed if we only estimate the homogenous or mean-based effects of Internet use and SAP adoption on farm income and household income (see Table A3 in the Appendix S1). Specifically, Table 6 shows that Internet use is positively and significantly associated with household incomes at the 50th and 75th quantiles, and the largest effect of Internet use on household income occurs at the higher quantile.[4] Internet use can support the development of farm and off-farm business through the potential channels of mobile money and remittance, which finally contribute to an increase in household income (Sekabira and Qaim 2017). The finding of the positive impact of Internet use on household income is consistent with the literature (Chang and Just 2009; Roodman *et al.* 2009; Ma *et al.* 2018b). For example, Chang and Just (2009) find that Internet access increases household income in Taiwan. Using cross-country panel data from 207 countries from the period 1991-2000, Roodman *et al.* (2009) also show that there is a positive association between Internet use and economic growth. However, Internet use does not affect farm income significantly.

SAP adoption is negatively and significantly associated with farm income at the 25th and 75th quantiles, with the highest negative effect occurring at the higher quantile. The finding is beyond our expectation, because, in essence, SAP adoption is expected to enhance farm economic performance. For example, the study by Adolwa *et al.* (2019) shows that integrated soil fertility management adoption significantly increases crop yields in both Ghana and Kenya (high crop yields usually translate into increased farm income). Some potential reasons can help explain the negative relationship between SAP adoption and farm income. Adoption of organic soil amendments such as organic fertiliser and farmyard manure (i.e. two important components of SAPs in our case) improves the soil fertility; however, it affects the evolution of soil quality and agricultural productivity over time (Ma *et al.* 2018a). Pollution-free pesticide application and IPM technology adoption might be not enough to eliminate pests because of pesticide resistance. Without investing or investing insufficient yield-increasing inputs such as chemical fertiliser and pesticide in short-term would result in yield loss and a lower farm income. The lower intensity of SAP adoption may also affect farm

[4] Because predicted Internet use variable and SAP adoption variable are used in the UQR model estimations, their proportional effects on farm income and household income could not be calculated directly using the formula $p_i = [exp(\alpha_i) - 1]$.

performance negatively because we show (Figure 1) that only 13.04% of the sampled households have adopted 4 types or more SAPs in practice.

SAP adoption has a significant and negative impact on household income at the selected quantiles. The absolute magnitude of the coefficient increases monotonically per quantile, suggesting that rural households with higher household income benefit less from adopting the SAPs in China. The negative association between SAP adoption and household income can be partially explained by the negative impact of SAP adoption on farm income. Another possible reason is that SAP adoption requires households to trade-off time allocation between farm work and off-farm work. However, allocating more time to SAP adoption would result in less time being allocated to off-farm work, and this reduces off-farm income (an important component of household income for rural farmers).

Among other factors that affect farm income and household income, we show that the age of the head contributes significantly to higher household income. An additional year increase in age tends to increase household income per capita by 1.2% at the 25^{th} quantile and by 1.5% at the 50th quantile. Age can be seen as a proxy for farmer's experience, job-related skills and managerial ability. Therefore, more experienced and skilled farmers are more likely to receive a high household income. Relative to female household heads, the males are associated with lower household income. The significant and negative coefficients of family size variable in the second and fourth columns of Table 6 suggest that an additional increase in family member decreases farm income by 8.8% at the 25^{th} quantile and by 16.6% at the 75^{th} quantile. In addition, the decreases in per capita household income due to an additional increase in family member range between 6.8% at the 25^{th} quantile and 10.6% at the 75^{th} quantile. Although larger households may be endowed with more labour endowments, they reduce farm income per capita and household income per capita.

The estimated coefficients of the farm size are positive and statistically significant in columns 2-7, suggesting that large farm size contributes to increases in both farm income and household income. In particular, the results presented in Table 6 indicate that an additional unit (i.e. mu) increase in farm size increases farm income by 3.1 - 6.9%, and it increases household income by 1.2 - 2.5%. The positive association between farm size and rural incomes has also reported in other studies (Kabunga *et al.* 2014; Liu *et al.* 2019). Membership variable in the fourth column of Table 6 has a positive and statistically significant coefficient, suggesting that for households who are cooperative members, the increase in farm income at the 75th quantile is around 154% ($exp[0.933] - 1$). The finding of the positive relationship between cooperative membership and farm income is consistent with the finding in the previous studies (Kabunga *et al.* 2014).

Obtaining remittance from household members is associated with an increase in household income. Our results indicate that the increases in household income contributed by remittance range from 16.4%

($exp[0.152]-1$) at the 25th quantile to 24.36% ($exp[0.218]-1$) at the 75th quantile. In addition to affecting household income directly, remittance can indirectly affect household income by affecting the adoption of new agricultural technologies and farm income (de Brauw and Rozelle 2008). For example, remittance relaxes capital constraints facing rural households and allows them to purchase yield-enhancing inputs (e.g. fertilisers and modern varieties), which finally increases crop yields and farm income. Finally, our estimates show that relative to farm households in Fujian (reference group), those in Henan receives 33.6% ($exp[0.290]-1$) more household income at the 25th quantile. The findings suggest the presence of location fixed effects that affect farm income and household income.

5. Conclusions and policy implications

Although numerous studies have shown SAP adoption enables to enhance farm economic and environmental performance, little is known about whether Internet use in rural areas can increase the SAP adoption. This paper analysed the impact of Internet use on SAP adoption, using an ETPR model that takes into account the possible selection bias due to the unobservables associated with Internet use. We also employed a UQR model to estimate the heterogeneous effects of Internet use and SAP adoption on farm income and household income.

The empirical results showed that Internet use exerts a positive and statistically significant impact on Internet use. In particular, we show that, on average, Internet users adopt 2.941 times more SAPs than non-users. The finding of the positive impact of Internet use on SAP adoption is further confirmed by the results of the ATE and ATT estimates. In addition to Internet use, we showed that the number of SAPs adopted by rural households is also positively and significantly determined by cooperative membership, remittance and environmental performance. Regarding the factors that affect Internet use, our results obtained from the first-stage estimation of the ETPR model showed that farmers' decisions to use the Internet are mainly driven by gender and education of household heads, family size, asset ownership and the presence of logistic service in a village.

The results estimated from the UQR model revealed that the joint effects of Internet use and SAP adoption on farm income and household income are heterogeneous and statistically different. In particular, Internet use is positively and significantly associated with household incomes at the 50th and 75th quantiles, and the largest effect of Internet use on household income occurs at the higher quantile. SAP adoption is negatively and significantly associated with farm income at the 25th and 75th, and it also negatively and significantly affects household income at the selected quantiles, with both of them the highest negative effect occurring at the higher quantile). Farm income was also positively affected by farm size and cooperative membership, while household income was affected positively by age, farm size and remittance.

The findings that Internet use increases SAP adoption highlight the importance of promoting Internet use in rural areas. This indicates that to promote the adoption of SAP, the policymakers could provide some information through the Internet as well as the investment on Internet accessibility. Our findings that Internet use only affects household income but does not affect farm income suggest that there is a necessity to facilitate innovative agricultural technological adoption via Internet-based extension programmes. The findings of the negative effects of SAP adoption on both farm income and household income underscore the importance of providing agricultural training programmes to help enhance farmers' knowledge about the benefits associated with SAPs and how to adopt the technologies appropriately in practice. Promoting farmers to access to ICT-based SAP information can be an effective strategy.

Different SAPs may affect sustainable agricultural production differently. For example, organic soil amendments such as organic fertiliser and manure build in soil nutrients and improve soil fertility over time. Besides, the adoption rate of some SAPs is quite low. For example, our descriptive results in Table 1 show that less than 4% of farmers in our samples have harmlessly treated agricultural films. Thus, in their efforts to promote the adoption of SAPs among rural households, the government can collaborate with agricultural cooperatives or farmer field schools to train farmers and help them better understand the necessities and functions associated with each SAP.

This study has some limitations. Our analysis may have omitted variable issue because we have focused on general farm income, without considering the differences in farm systems. Thus, future studies may investigate how Internet use affects farm income of a specific crop or livestock production. Moreover, as each SAP may play a different role in affecting farm income and household income, the estimations that rely on only SAP adoption intensity would encounter problems of information loss. Thus, future studies may use a multinomial endogenous switching regression model, which has the ability to account for multiple SAP adoption choices, to analyse how farmers' choices of the individual and combined SAPs affect farm outputs.

Data availability statement

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

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Supporting Information

Additional Supporting Information may be found in the online version of this article:

Appendix S1 Pearson correlation analysis for testing the validity of the instrumental variable.