The Joint Effects of Off-farm Work and Smartphone Use on Household Income in Rural China

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Abstract:

This paper assesses the impact of participation in off-farm work on smartphone use, using an endogenous switching probit model and a survey of 493 rural Chinese households. The joint impacts of off-farm work participation and smartphone use on household income are also analyzed using a control function method. The results show that participation in off-farm work increases the probability of smartphone use significantly. Furthermore, we find that the household heads who engaged in off-farm activities and who were smartphone users earned 3,430 Yuan and 2,643 Yuan more per capita annual income, respectively, compared to their full-time farming and smartphone-free counterparts.

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JEL Codes: J22, I31

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Keywords: Off-farm work; Smartphone use; Household income; Endogenous switching probit; Control function method; Rural China

JEL classification: C21; J22; I31; L86

1. Introduction

Recent evidence suggests that China has the highest smartphone penetration rate (the proportion of smartphone users to total population) worldwide. It was estimated that China's smartphone penetration rate was 68 per cent in 2015 whilst in comparison to an average rate of 55 per cent across European countires (Jing 2017). Relative to traditional mobile phones, smartphones can provide remote video communication, facilitate online payment and financial transfer, enable entertainment activities, and easy access to diverse information.[1] Therefore, the usage of smartphones might foster economic development, especially in rural regions.

Recent studies have highlighted the significant role smartphones play in increasing rural household income and supporting local employment and commuting (Hartje and Hübler 2017; Hübler and Hartje 2016). Using the data from the rural Southeast Asian Mekong region, Hübler and Hartje (2016) find that smartphone ownership exerts a positive and significant effect on per capita income. As rightly point out by Acker and Mbiti (2010), mobile devices including smartphones may generate income gains by facilitating the delivery of financial, agricultural, health, and educational services, enhancing agricultural products and job market participation, expanding social networks, and reducing households' exposure to risk. Despite the benefits associated with smartphones, Sylvester (2013) reveals that the adoption rate of smartphones in rural regions of developing countries remains low, due primarily to low income levels. From a perspective of development policy, income enhancement and diversification strategies could therefore increase smartphone use in rural areas with subsequent economic benefits.

Despite the welfare improvement of rural residents has been a priority targeted by the Chinese rural policies, it is still a long-standing social problem that rural households are

[1] A traditional mobile phone can only be used for "voice" communication and text/SMS, while a smartphone is characterized by a touch-screen, Internet access and software applications (Hartje and Hübler 2017).

disadvantaged by China's widening urban-rural income inequality. One way to diversify and increase rural incomes is through off-farm work. A large body of literature has confirmed the positive role of off-farm work in mitigating income variability and rural poverty and increasing food consumption expenditure (see, for instance, Chang and Mishra, 2008; Hoang et al., 2014; Janvry and Sadoulet, 2001; Mishra et al., 2015; Mishra and Goodwin, 1997; Reardon et al., 2000; Su et al., 2016; Willmore et al., 2012; Zhu and Luo, 2010). In their analysis on Mexico, Janvry and Sadoulet (2001) note that participation in off-farm activities contributes to greater equality in the distribution of income. Mishra et al. (2015), however, find that income from off-farm activities significantly increases food consumption expenditures of rural Bangladesh households. Agricultural household/production theory also suggests that off-farm work relaxes farmers' liquidity constraints through the income effect and enables them to purchase farm inputs (see, for instance, Kousar and Abdulai, 2015; Taylor et al., 2003). Davis et al. (2009) review the existing literature on developing trends in rural off-farm employment and its impacts on farm technology choices and agricultural modernization and diversification. They conclude that rural off-farm employment has positive impacts on farm purchased inputs and capital investment in Bulgaria, Mexico, Nigeria, the Philippines, Senegal, and Vietnam. Given the solid evidence of the positive effects of off-farm work on rural economic development, we assume that off-farm work may play a much larger role in improving the living standards of rural households.

In theory, off-farm work, by raising incomes, can have a direct impact on smartphone use in rural areas and the use of these smartphones can further enhance incomes. For instance, Huebler (2016) finds that migration in terms of off-farm work participation facilitates mobile technology diffusion and dispersion in Thailand, Vietnam, Laos, and Cambodia. Therefore, understanding the linkage between off-farm work participation and smartphone use has important policy implications, especially for the rural economic advancement in developing countries. However, whether and to what extent participation in off-farm work affects farmers' decisions to use smartphones remains unclear.

The aim of this paper is to examine the impact of participation in off-farm work on smartphone use, as well as the impacts of off-farm work participation and smartphone use on household income. We employ the household-level data of 493 farmers in rural China. These farmers are either off-farm work participants or non-participants. In particular, both of them are either smartphone users or non-users.

The paper extends the prior literature on off-farm work and adoption of ICTs in developing countries on three major fronts. First, we provide the first study examining the effect of off-farm work on smartphone use in rural China. Given that Chinese smartphone users (especially those residents in rural areas) are novices and can be regarded as "digital immigrants" (Prensky 2001), it is therefore important to examine how off-farm work participation boosts smartphone use in rural China. Second, this paper uses an endogenous switching probit model to identify the relationship between off-farm work participation and smartphone use. The model enables investigation of the factors that influence farmers' decisions to participate in off-farm work and the determinants of smartphone use separately for off-farm work participants and non-participants while controlling for other household and farm-level characteristics. Furthermore, it estimates consistent treatment effects of off-farm work participation on smartphone use by addressing the selection bias arising from both observed and unobserved heterogeneities (Ayuya et al. 2015; Lokshin and Sajaia 2011; Manda et al. 2016). The results estimated from a recursive bivariate probit model are also presented to provide a further understanding of the impact of off-farm work participation on smartphone use.

Third, we employ a control function method to examine the joint effects of off-farm work participation and smartphone use on household income. Some studies have examined the effect of off-farm work on household income (e.g., Janvry and Sadoulet, 2001; Owusu et al., 2011), however, to the best of our knowledge, with the notable exception of Hübler and Hartje (2016), no work has focused on the nexus between smartphone use and household income. In particular, there is little knowledge concerning the joint role of off-farm work participation and smartphone use in affecting household income.

The rest of the paper is structured as follows. Section 2 presents the estimation strategies. Section 3 presents the data and descriptions of study variables. The empirical results are discussed in Section 4. Section 5 concludes.

2. Estimation strategies

2.1 Impact of participation in off-farm work on smartphone use

2.1.1 Impact assessment and selection bias

The first objective of this study is to analyze the effect of participation in off-farm work on smartphone use. Previous studies have shown that off-farm work participants and non-participants are systematically different, mainly because farmers themselves decide whether or not to participate in off-farm work (self-selection) (Abdulai and Delgado 1999; Kousar and Abdulai 2016; Owusu et al. 2011; Zhu and Luo 2010). When off-farm work is not randomly distributed, farmers' off-farm work participation decisions are likely to be influenced by both observable factors (e.g., age, education and household size) and unobservable factors (e.g., innate abilities, motivation and climate uncertainty) that may be correlated to the outcome (i.e. smartphone use in our case) of interest. This fact results in a sample selection and endogeneity issue, which needs to be addressed in order to obtain an unbiased and consistent estimation of the treatment effect of off-farm work participation on smartphone use.

Econometric techniques to deal with selection bias in the case of a binary outcome variable (here the smartphone use status of household heads) encompass propensity score matching (PSM), recursive bivariate probit (RBP) model and the endogenous switching probit (ESP) model. It is worth highlighting that, however, PSM only controls for observed heterogeneity (Dehejia and Wahba 2002). The RBP model has the ability to address the selectivity bias taking into account both observed and unobserved heterogeneities and estimates the direct impact of off-farm work on smartphone use, although this model assumes that the impact can be represented as a simple parallel shift with respect to the outcome variable (Chiburis et al. 2012; Thuo et al. 2014). By contrast, the ESP model enables reduction of the selection bias by controlling for both observed and unobserved heterogeneities, and it relaxes the assumption of the RBP model and estimates two separate outcome equations (one for off-farm work participants and another for non-participants) in addition to the selection equation (Lokshin and Sajaia 2011). For these reasons the ESP model was selected to estimate the effect of off-farm work on smartphone use.

2.1.2 The ESP model

In the ESP model, the decision to participate in off-farm work and its impact on smartphone use can be modeled in a two-stage treatment framework. In the first stage, farmers' decision to participate in off-farm work is modeled and estimated using a probit model.[2] Following a random utility maximization framework, the households choose to participate in off-farm work if the utilities gained from the participation are greater than the utilities gained from non-participation.[3] Thus, a farm household's decision to participate in off-farm work can be expressed in a discrete choice model. The specification of this model is：

$$T_i^* = \gamma_i Z_i + \varepsilon_i, \; T_i = 1\,(T_i^* > 0) \tag{1}$$

[2] Given the fact that household heads dominate decision making in a household, and their participation in off-farm work and smartphone use have the most impact on the household, we follow Phimister and Roberts (2006) and focus on the off-farm work participation and smartphone use of the household heads rather than other household members in the present study.

[3] This assumption is equivalent to the one that assumes a household head decides to work off the farm if the market wage is higher than its reservation wage for farm and leisure time (see, for example, Ghimire et al., 2014; Owusu et al., 2011).

where T_i^* is a latent variable which represents the probability of the household head to work off the farm, which is determined by the observed binary variable T_i that takes the value 1 for off-farm work participants and 0 for non-participants; Z_i is a vector of explanatory variables (e.g., age, education and household size); γ_i is a vector of parameters to be estimated, and ε_i is an error term with mean zero and normal distribution.

In the second stage, the two outcome equations representing smartphone use functions respectively for off-farm work participants and non-participants, conditional on the choice of off-farm work participation, are given as:

$$Y_{1i}^* = \alpha_1 X_{1i} + \delta_{1i},\ Y_{1i} = 1\ (Y_{1i}^* > 0) \quad T_i = 1 \tag{2a}$$

$$Y_{0i}^* = \alpha_0 X_{0i} + \delta_{0i},\ Y_{0i} = 1\ (Y_{0i}^* > 0) \quad T_i = 0 \tag{2b}$$

where Y_{1i}^* (Y_{0i}^*) is a latent variable that determines the propensity of a household head to use a smartphone if he/she (does not) participate(s) in off-farm work; X_{1i} and X_{0i} are vectors of exogenous variables; α_1 and α_0 are vectors of parameters to be estimated; and δ_{1i} and δ_{0i} are error terms. In an ESP model, a maximum likelihood estimator can be used to estimate equations (1), (2a) and (2b) jointly (Lokshin and Sajaia 2011).

To rule out the potential endogeneity of off-farm work participation, the ESP model requires the inclusion of at least one instrumental variable in the first-stage estimation, thereby fulfilling the exclusion restriction (Lokshin and Sajaia 2011). In our case, a variable representing the household head's perception of whether it is possible to get off-farm work opportunities through social networks (e.g. friends, relatives and neighbors) (1 = "Yes", 0 = "No") is used as an instrument, which is assumed to significantly influence the household head's off-farm work participation decision, but does not directly affect his or her smartphone use. To test the validity of the perception variable as an instrument, we ran simple probit models for the off-farm work participation equation and two smartphone use equations with inclusion of the instrument as a regressor. The results, which are available on request, show that the perception variable has a statistically significant impact on off-farm work participation but does not affect smartphone use, even at the 10 per cent significance level. We thus confirm the validity of our instrument.

The estimations of α_1 and α_0 using the probit regression model might lead to biased estimates because the expected values of the error terms (δ_{1i} and δ_{0i}), conditional on the off-farm participation criterion, are non-zero. It is assumed that δ_{1i}, δ_{0i} and ε_i are jointly normally distributed, with a mean-zero vector and correlation matrix:

$$\Omega = \begin{pmatrix} 1 & \rho_0 & \rho_1 \\ & 1 & \rho_{10} \\ & & 1 \end{pmatrix} \tag{3}$$

where ρ_0 and ρ_1 are the correlations between ε_i and δ_{1i} and ε_i and δ_{0i}, respectively; ρ_{10} is the correlation between δ_{1i} and δ_{0i}. Note that Y_{1i} and Y_{0i} can not be observed simultaneously, and that the joint distribution of (δ_{1i}, δ_{0i}) is not identified, thus ρ_{10} cannot be estimated. It is worth mentioning that the significance of ρ_0 and/or ρ_1 suggests the presence of selection bias arising from unobserved factors (Lokshin and Sajaia 2011).

2.1.3 Estimating treatment effects

The ESP estimate highlights the important factors that influence farmers' decisions to participate in off-farm work and to use smartphones. However, some further estimations are required in order to identify the true effect of participation in off-farm work on smartphone use. In particular, after estimating the model's parameters implied in equations (1), (2a) and (2b), the average treatment effect on the treated (ATT) and the average treatment effect on the untreated (ATU) can be calculated (Lokshin and Sajaia 2011):

$$\mathrm{ATT} = \frac{1}{N_P}\sum_{i=1}^{N_P}\{\Pr(Y_{1i} = 1|T = 1, X = x) - \Pr(Y_{0i} = 1|T = 1, X = x)\}$$

$$= \frac{1}{N_P}\sum_{i=1}^{N_P}\left\{\left\{\frac{\Phi_2(\alpha_{1i}X_{1i}, \gamma_i Z_i, \rho_1) - \Phi_2(\alpha_{0i}X_{0i}, \gamma_i Z_i, \rho_0)}{F(\gamma_i Z_i)}\right\}\right\} \tag{4a}$$

$$\text{ATU} = \frac{1}{N_N}\sum_{i=1}^{N_N}\{\Pr(Y_{1i} = 1|T = 0, X = x) - \Pr(Y_{0i} = 1|T = 0, X = x)\}$$

$$= \frac{1}{N_N}\sum_{i=1}^{N_N}\left\{\left\{\frac{\Phi_2(\alpha_{1i}X_{1i},\gamma_i Z_i,\rho_1) - \Phi_2(\alpha_{0i}X_{0i},\gamma_i Z_i,\rho_0)}{F(-\gamma_i Z_i)}\right\}\right\} \quad (4b)$$

where Φ_2 is a cumulative function of a bivariate normal distribution and F is a cumulative function of a univariate normal distribution. N_P is the number of treated individuals (T = 1), and N_N is the number of untreated individuals (T = 0). ATT (ATU) refers to the expected effect of the treatment on individuals with observed characteristics X who (did not) participate(d) in off-farm work. After correcting for selection bias arising from both observed and unobserved factors as discussed previously, the ATT and ATU estimates are unbiased.

2.2 Impact of off-farm work and smartphone use on household income

The second objective of this study is to analyze the effect of off-farm work participation and smartphone use on per capita household income. For analytical purposes, we assume that household income is a linear function of a vector of explanatory variables (X_i) along with two dummy variables (T_i, S_i) representing household heads' decisions to work off the farm and to use smartphones. The regression equation for household income can be specified as:

$$H^p = \varphi_i T_i + \nu_i S_i + \varsigma_i X_i + \mu_i \quad (5)$$

where H^p represents per capita household income; T_i is a dummy variable for off-farm work participation (1=participant; 0=non-participant), and S_i is a dummy variable for smartphone use (1=smartphone user; 0=smartphone non-user); X_i is a vector of exogenous variables; φ_i, ν_i and ς_i are parameters to be estimated; and μ_i is an *i.i.d.* error term.

Since it is an autonomous decision by household heads whether to participate in off-farm work and to use smartphones, the unobservable variables might be correlated with both the two decisions and the level of household income, thereby leading to an endogeneity issue. To resolve the endogeneity issue, both the instrumental variable method and the control function method have been proposed. Although both of these methods generate consistent estimates, the control function method is a more efficient estimator (Chang and Mishra 2008; Vella and Verbeek 1999). Therefore, we use the control function method to estimate the effect of off-farm work participation and smartphone use on household income.

The control function method contains two stages. In the first stage, the decision to work off-farm and the decision to use smartphone are jointly estimated using a seemingly unrelated bivariate probit (SUBP) model. The specification describing the off-farm work choice of household heads is presented in equation (1). Following Hübler and Hartje (2016), the decision of a household head to use smartphone can be expressed as follows:

$$S_i^* = \varrho_i X_i + \upsilon_i,\ S_i = 1\ (S_i^* > 0) \quad (6)$$

where S_i^* is a latent variable which represents the probability of the household head to use smartphone, which is determined by the observed binary variable S_i that takes the value 1 for smartphone users and 0 for non-users; X_i is a vector of explanatory variables; ϱ_i is a vector of parameters to be estimated, and υ_i is an error term with mean zero and normal distribution.

The SUBP model estimates the equations (1) and (6) jointly. The inverse Mills ratios (IMR) are then predicted and added as extra variables in the second stage regression of the household income equation (5) in addition to the set of explanatory variables (Chang and Mishra 2008). The household income equation used in the empirical estimation can be re-written as:

$$H^p = \xi_i T_i + \varpi_i S_i + \beta_i X_i + \kappa_i (IMR_{off-farm}) + \vartheta_i (IMR_{smartphone}) + e_i \quad (7)$$

where H^p is the per capita household income; T_i and S_i are dummies that specify the decision to work off the farm and the decision to use a smartphone, respectively; The estimated parameters (ξ_i, ϖ_i) capture the effects of these two decisions on household income; X_i represents exogenous variables and β_i denotes estimated parameters; $IMR_{off-farm}$ and $IMR_{smartphone}$ are IMRs predicted from the SUBP model, which are used to account for potential treatment selection bias stemming from unobserved factors; e_i is an *i.i.d.* error term.

3. Data and descriptive statistics

The data used in the present study were collected through a recent household survey conducted in January 2017 in rural China. A multistage sampling procedure was used to select farmers. First, Gansu province in Western China, Henan province in Central China, and Shandong province in Eastern China were randomly selected. These three provinces have different geographical and socioeconomic conditions at regional levels. Second, Dingxi city in Gansu, Sanmengxia city in Henan, and Heze city in Shandong were randomly selected. Third, three villages in each city were randomly selected, resulting in a total sample of 493 households. Of the 493 respondents, 351 engaged in off-farm work, 318 used smartphones, and 248 farmers participated in off-farm work and also used smartphones (see Table 1). The survey collected a range of information including household and farm-level characteristics, asset ownership, cooperative membership, off-farm work participation and smartphone usage.

Table 2 presents the definitions and descriptive statistics of the variables used in the present study. In particular, a household head is defined as an off-farm work participant if he/she has migrated to a location outside his/her village to work or works in the local regions and lives in his/her village. The survey showed that approximately 71% of household heads participated in off-farm work and 65% of household heads used smartphones. The average per capita annual household income was 12,150 yuan (equivalent to 1,787 USD).[4] The average age of household heads was approximately 47 years, where the mean of years of schooling was about 6.78 years. The mean land area cultivated by households was 7.17 mu (equivalent to 0.48 hectare). In our sample, only 3 per cent of households are members of agricultural cooperatives.

The mean differences in the demographic and socioeconomic characteristics between

[4] Yuan is Chinese currency, and 1 USD=6.80 yuan in 2017.

off-farm work participants and non-participants are presented in Table 3. It shows that relative to non-participants, off-farm work participants are generally younger and have higher education levels. Off-farm work participants are more likely to be males. There is also a significant difference with respect to farm size, 6.71 mu for off-farm work participants versus 8.33 mu for non-participants, suggesting that off-farm work participants operate on smaller farm sizes compared with non-participants. Table 3 also reveals that those working off-farm are 44.90 per cent more likely to use smartphones compared to those who do not work off-farm. On average, the per capita household income for off-farm work participants is 56.94 per cent higher than that for their counterparts. However, it is worth mentioning that these difference does not account for the effect of other farmer characteristics and thus cannot be taken as ultimate outcomes.

4. Empirical results

In this section, we present and discuss the results estimated from the empirical models. In particular, the estimates of the determinants of off-farm work participation and the determinants of smartphone use for participants and non-participants are presented in Table 4. As indicated previously, the maximum likelihood approach is used to estimate both the off-farm work participation and two smartphone use equations simultaneously. Table 5 presents the results for the treatment effects of participation in off-farm work on smartphone use. The results regarding the impacts of off-farm work participation and smartphone use on household income are estimated using a control function method and presented in Table 6.

4.1 Determinants of off-farm work participation

The results representing the determinants of off-farm work participation are given in the second column in Table 4. The results show the life-cycle effect on the likelihood of off-farm work participation is quadratic. At younger ages, an increase in age increases the probability of off-farm work participation with the maximum effect occurring at just over 41 years. At older ages, the likelihood of participating in off-farm work decreases as age increases. These results are consistent with the findings of Abdulai and Delgado (1999) for Ghana and Chang and Mishra (2008) for the USA. Gender appears to be an important factor that affects off-farm work participation. Relative to female household heads, the males are more likely to participate in off-farm work. The finding is echoed by Wang et al. (2016), who investigated the relationship between gender and off-farm employment and found that the off-farm work participation rates of males are higher than the participation rates of females in China. The significant and positive impact of education suggests that better educated household heads have a significantly higher probability of engaging in off-farm work, which is in line with Janvry and Sadoulet (2001) and Zhang et al. (2002) who found that education played an essential role in accessing better remunerated off-farm employment. Ghimire et al., (2014) also pointed out that more educated heads of household can better identify and process the information associated with off-farm activities.

The variable representing whether a school student is present in the household is negative and statistically significant, perhaps suggesting that the presence of senior school student in a household decreases the likelihood of off-farm work participation. The finding is supported by the fact that household heads are less likely to work off farm in order to fully support their senior school children who usually have pressures due to the highly competitive environment for university entry in China. Available evidence from China also revealed that the educational performance of children is adversely affected by parental migration (see, for example, Zhou et al. 2014). Farm size has a negative and significant impact on off-farm work participation of household heads. The finding of an inverse relationship between farm size and the probability of off-farm work participation is in line with the study on China by Wang et al. (2017). The significance of location variables suggests that, relative to farmers in Gansu, farmers in Henan are less likely to participate in off-farm work while those in Shandong are more likely to work off the farm. As expected, the variable serving as an instrument is positive and significant. It is worth emphasizing here that the primary objective of the off-farm work equation estimation at the first stage of the ESP model is to control for unobserved heterogeneities that may bias the effect of off-farm work participation on smartphone use.

4.2 Determinants of smartphone use

Results for the smartphone use equations are shown in the third and last columns of Table 4. The coefficient estimates for the off-farm work participants and non-participants regimes differ notably with respect to a number of variables, suggesting that the switching regression approach is preferred over a simple RBP model. The gender of the household heads appears to have different impacts on smartphone use for off-farm participants and non-participants. The positive and significant coefficient of gender for participants indicates that for this group of farmers, male off-farm work participants are more likely to use smartphones. For non-participants, female household heads are more prone to use smartphones. Household size has a positive and significant impact on smartphone use among non-participants, but has no such impact among off-farm work participants. One possible explanation is that smartphones are more likely to be used by the household heads with larger families to communicate with the other family members when they are not engaged in off-farm activities.

The variable representing a school student in the household has a positive and statistically significant impact on smartphone use for non-participants, but no impact for off-farm work participants. The rationale is that smartphone facilitates the interactive communication between household heads (as parents) with teachers of their children and peer parents, only among the farmers who spend less time on off-farm activities. The coefficients of farm size are positive for both off-farm work participants and non-participants, but only statistically significant for non-participants. The observation suggests that non-participants with a large farm size are more likely to use smartphones. Non-participants of off-farm work rely more on incomes from agricultural production and marketing, while smartphone use facilitates their contact with input dealers and output buyers, particularly for those who cultivate large farms.

In both specifications, the coefficients of membership variable are positive and statistically significant, perhaps implying that membership in agricultural cooperatives increases the probability of smartphone use for both off-farm work participants and non-participants. As stated by Fischer and Qaim (2012), cooperative organizations can easily contact their members through mobile phones with respect to production and marketing information and group activities, especially when households are not located in the close villages. Ownership of assets such as a digital camera appears to increase the likelihood of smartphone use of off-farm work participants and non-participants, suggesting that better-off farmers are more likely to afford smartphones. This finding is in line with Hartje and Hübler (2017) who indicate that tangible assets have positive impacts on smartphone use. The better quality of road from village to local transportation stations is positively and significantly correlated with smartphone use of off-farm work participants. The results also reveal that location fixed effects may be significant in explaining differences in smartphone use in rural China. In particular, relative to farmers in Gansu (reference province), off-farm work participants located in Henan and Shandong tend to have a higher probability of using smartphones, while those non-participants in Shandong are less likely to use the mobile device.

In the lower part of Table 4, we present estimates of the selectivity correction terms (ρ_1 and ρ_0), which measure the correlations between the error terms in the off-farm work participation equation and in the smartphone use equations. The coefficients of ρ_1 and ρ_0 are statistically significant, suggesting that participation in off-farm work may not have the same effect on non-participants, should they decide to participate. Notably, the negatives signs of ρ_1 and ρ_0 imply negative selection bias arising from unobserved heterogeneities (Lokshin and Sajaia 2011; Manda et al. 2016). Failure to deal with this bias may lead to biased estimates of the effect of off-farm work participation on smartphone use. Moreover, the Wald test for $\rho_1 = \rho_0 = 0$ indicates that the null hypothesis that the off-farm work variable is exogenous can be rejected. Generally, these findings justify the use of the ESP model to identify the factors that influence household heads' decisions to participate in off-farm work and use smartphones, as well as to estimate an unbiased treatment effects of off-farm work.

4.3 Treatment effects of off-farm work on smartphone use

We now use the coefficient estimates from the ESP selection and outcome equations in combination with equations (4a) and (4b) (see section 2.3) to calculate the treatment effects of off-farm work on smartphone use. Both ATT and ATU are calculated and shown in Table 5. The ATT, which is the actual effect that participants experience through off-farm work participation, is positive and statistically significant. The finding suggests that the causal effect of off-farm work participation significantly increases the probability of smartphone use by 54.7 percentage points. The positive and significant ATU implies that for those not working off-farm, the probability of using smartphones would increase by 24.4 percentage points if they chose to participate in off-farm work. This observation is consistent with Huebler (2016) who found that international and rural-urban migration occurring in Thailand, Vietnam, Laos, and Cambodia had a positive and significant impact on mobile phone ownership. Linh et al. (2016) also confirmed that off-farm employment is one of the most important factors explaining the use of media and personal information sources (including mobile phones) in Vietnam. Our findings provide evidence that an increase in the number of farmers with off-farm jobs would facilitate the adoption of updated ICTs such as smartphones.

Given the significant impact of gender on off-farm work participation and smartphone use, it is useful to examine the extent that gender is related to the effect of off-farm work on smartphone use. We therefore disaggregate the treatment effects of off-farm work by gender, and present the results in Table 5. The results show that off-farm work participation of male household heads has a larger effect on smartphone use than that of female household heads. For example, the ATT estimates show that the causal effect of off-farm work increases the smartphone use for male household heads by 56.9 percentage points, while the effect for female household heads increases the likelihood of smartphone use by 40.8 percentage points.

The effects of participation in off-farm work on smartphone use by survey provinces are also identified in order to capture the regional fixed effects associated with off-farm work and smartphone use. The results presented in Table 5 show that participation in off-farm work has the largest effect on smartphone use for farmers in Shandong, which significantly increases the probability of smartphone use by 76.3 percentage points. Off-farm work increases the likelihood of smartphone use for farmers participating in off-farm work in Gansu and Henan by 31.3 and 53.4 percentage points, respectively. With respect to ATU estimates, our results show that non-participants in Henan and Shandong would be 29.2 and 41.5 percentage points more likely to use smartphones if they chose to participate in off-farm work.

Finally, we also present the results estimated from RBP model to provide a further understanding of the effect of participation in off-farm work on smartphone use. As indicated previously, the RBP model controls for selection bias arising from both observable and unobservable factors and estimates a direct impact of participation in off-farm work on smartphone use (Chiburis et al. 2012; Thuo et al. 2014). The results are presented in Appendix Table A1. The negative and statistically significant coefficient of ρ' confirms the presence of negative selection bias associated with unobservable factors, which is consistent with what was observed in Table 4. Since the magnitudes of the coefficients from RBP model are not straightforward, we therefore predict the marginal effects to ease the interpretation.

For brevity, we only present in the last column of Table A1 the marginal effects obtained from the smartphone use equation while that obtained from the off-farm work equation is available on request. The results clearly demonstrate that off-farm work has a positive and significant impact on smartphone use, with a marginal effect of 0.526. This may suggest that being an off-farm work participant, the probability of smartphone use would increases 52.6 percentage points. The findings generally confirm the positive role of off-farm work in increasing the likelihood of smartphone use in rural China.

4.4 Off-farm work, smartphone use and household income

The results of the effects of off-farm work participation and smartphone use on household income are presented in Table 6. As mentioned earlier, the SUBP model was used to jointly estimate the household heads' decisions to work off the farm and to use smartphones. It is worth mentioning here that the primary objective of the SUBP model estimation in this study is not to identify the factors that influence farmers' decision making, but serves as a control function to predict IMRs that control for selection bias. The results are presented in Appendix Table A2. The positive and significant coefficient of ρ'' suggests that the decisions of the household heads to work off the farm and to use smartphones are significantly interrelated (21.9 per cent). We adopt the Ordinary Least Square (OLS) model to estimate equation (7). The test value under the null hypothesis that these two IMRs (IMR_off-farm and IMR_smartphone) are jointly equal to zero is 9.41, which is significant at the 1 per cent level. The result provides evidence of the self-selection problem. Put another way, the results of this analysis will be biased if the endogeneity between the two decisions and household income is not corrected.

The result provides evidence that off-farm work participation and smartphone use of household heads are two important determinants of household income. In particular, the households engaged in off-farm activities earned 3,430 yuan more per capita annual income in comparison to the full-time farming counterparts. Likewise, smartphone use increased per capita income by 2,643 yuan. Our results are consistent with Hübler and Hartje (2016) who found that smartphone ownership significantly increased household income. Our results also lend support to the finding that the income effect is associated with off-farm work participation (Janvry and Sadoulet 2001; Kousar and Abdulai 2016; Taylor et al. 2003).

Other explanatory variables are also found to be significantly correlated with household income. Age of the household head is a variable that was included to capture the life cycle stage of the household. We find that the coefficient of age is positive and that of age squared is negative suggests the existence of nonlinearity in the age-household income relationship. In particular, younger household heads have higher household incomes than older household heads. The positive and statistically significant coefficient for gender suggests that male household heads have higher household income. The positive and statistically significant coefficient of education variable may imply that educated household heads tend to have higher household income. As highlighted by Janvry and Sadoulet (2001), the most remunerative employment opportunities are captured by those with the highest education levels. Thus, more educated households are wealthier. The coefficient of household size is negative and significantly different from zero, suggesting that larger household size reduces per capita household income. Although large household size may mean a greater labor supply, it appears to reduce per capita household income.

The coefficient of school student variable is negative and statistically significant, suggesting that the presence of senior school student in a household tends to have a negative and significant impact on household income. The estimates reveal that farm size exerts negative and significant impacts on household income of farming households. Also, regional differences exist in terms of household income such that household heads living in Shandong tend to be richer.

5. Conclusion

Studies that investigate the effect of off-farm work on the adoption of ICTs are relatively scarce. This paper aimed to fill this gap by examining the effect of off-farm work participation on smartphone use, drawing upon cross-sectional data of 493 rural households in China. An ESP model was employed to address the potential selectivity bias from both observed and unobserved factors. A control function method was also used to analyze the joint effects of off-farm work participation and smartphone use on household income. To the best of our knowledge, this is the first comprehensive study that identifies a statistical association between off-farm work and smartphone use and further examines the joint effects of off-farm work participation and smartphone use on household income.

The results of the ESP model estimation identified a negative selection bias, suggesting that the estimates of effects of off-farm work participation on smartphone use would be biased without adjusting for the sample selection bias due to self-selection of farmers in off-farm work activities. Adjusting for this bias, the results show that off-farm work participation has a positive and significant impact on smartphone use of rural households in China, which provides evidence that off-farm work can facilitate the adoption of information and communication technologies such as smartphones. In particular, the ATT estimates show the causal effect of off-farm work participation increases the probability of smartphone use by 54.7 percentage points. On the other hand, the positive and significant ATU suggests the farmers not participating in off-farm work would be 24.4 percentage points more likely to use smartphones if they did actually work off-farm. Further analysis reveals that off-farm work participation of male household heads has a relatively larger effect on the likelihood of smartphone use compared with their female counterparts. In addition, off-farm work exerts a larger effect on the probability of smartphone use of farmers in Shandong, relative to those in Gansu and Henan.

With respect to the factors that influence farmers' decisions to work off the farm and to use smartphones, the empirical results indicate that the decision to work off-farm by rural household heads in China is associated with age, gender, education, the presence of a school student in the household, and farm size. We also show that smartphone use decisions of off-farm work participants are affected by gender, cooperative membership, ownership of asset such as digital camera, and road condition. Gender, household size, the presence of a school student, farm size, cooperative membership and asset ownership are the main factors that determine the smartphone use decisions of those that do not work off-farm.

The econometric estimation with a control function method reveals that farmers have made decisions to work off-farm and to use smartphones jointly. In addition, we observe that both off-farm work participation and smartphone use have positive and significant impacts on household income. More specifically, the household heads who engaged in off-farm activities and who were smartphone users earned 3,430 yuan and 2,643 yuan more per capita household income, respectively, compared to their full-time and smartphone-free counterparts. All in all, our results support the evidence that off-farm work by raising incomes can increase the probability of smartphone use and the use of these smartphones can further enhance incomes.

We conclude that off-farm jobs can support rural smartphone use, which can actually increase household income and enhance rural development. Thus, relevant policies encouraging more off-farm jobs are in need to proliferate the adoption and diffusion of smartphones. Given that off-farm work participation of male household heads contributes to a higher likelihood of smartphone use, the policy designs should provide more opportunities for women to work off the farm and then increase the probability of smartphones among this group of farmers, which may boost overall living standards of rural households. This is supported by the fact that labor markets are not gender-neutral and the males have more opportunities in terms of off-farm work activities than the females, as evidenced by Wang et al. (2016). The finding of the positive and significant impact of smartphone use on household income suggests that governments in rural areas may think to provide related training for local residents and to roll out necessary measures and services to guide the usage of smartphones, which can be seen as a rural income-enhancing strategy.

Finally, given that studies investigating the nexus between off-farm work participation and adoption of ICTs remain scarce, further exploration is needed to clarify the underlying mechanisms through which off-farm work impacts on smartphone use. It would also be important for future research to investigate how participation in off-farm work affects adoption of other modern ICTs such as the internet in rural areas of developing countries.

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Table 1 Sample distribution by off-farm work participation and smartphone use

Category	Participants of off-farm work	Non-participants of off-farm work	Total
Users of smartphones	248	70	318
Non-users of smartphones	103	72	175
Total	351	142	493

Table 2 Definition and descriptive statistics

Variables	Definition	Mean (S.D.)
Dependent variables		
Off-farm work	1 if a household head participated in off-farm work in 2016, 0 otherwise	0.71 (0.45)
Smartphone use	1 if a household head uses a smartphone, 0 otherwise	0.65 (0.48)
Household income	Per capita household income (yuan/1000)	12.15 (8.45)
Independent variables		
Age	Age of household head (in years)	46.79 (10.32)
Gender	1 if a household head is male, 0 otherwise	0.84 (0.37)
Education	Years of schooling of household head (in years)	6.78 (2.76)
Household size	Number of people residing in household	4.55 (1.45)
Vehicle	1 if a household owns a farming vehicle, 0 otherwise	0.65 (0.48)
School student	1 if a household has senior school students, 0 otherwise	0.16 (0.36)
Farm size	Total farm size (in mu)[a]	7.18 (6.01)
Membership	1 if a household has cooperative membership, 0 otherwise	0.03 (0.17)
Digital camera	1 if a household has digital camera, 0 otherwise	0.04 (0.19)
Road condition	1 if the quality of road from village to the nearly transportation stations is good, 0 otherwise	0.75 (0.43)
Gansu	1 if a household is located in Gansu province, 0 otherwise	0.33 (0.47)
Henan	1 if a household is located in Henan province, 0 otherwise	0.34 (0.48)
Shandong	1 if a household is located in Shandong province, 0 otherwise	0.33 (0.47)
Perception	1 if a household head perceives it is possible to get off-farm work opportunities through social networks (e.g., friends, relatives and neighbors), 0 otherwise	0.75 (0.43)

[a] 1 mu=1/15 hectare; S.D.=standard deviation.

Table 3 Mean differences in demographic and socioeconomic characteristics between off-farm work participants and non-participants

Variables	Participants	Non-participants	Mean difference
Age	45.40 (1.00)	50.23 (0.53)	-4.829***
Gender	0.86 (0.04)	0.77 (0.02)	0.096***
Education	7.11 (0.27)	5.96 (0.14)	1.143***
Household size	4.52 (0.14)	4.62 (0.07)	-0.096
Vehicle	0.66 (0.05)	0.65 (0.03)	0.007
School student	0.15 (0.04)	0.18 (0.02)	-0.028
Farm size	6.71 (0.59)	8.33 (0.28)	-1.619***
Membership	0.03 (0.02)	0.02 (0.01)	0.010
Digital camera	0.04 (0.02)	0.03 (0.01)	0.015
Road condition	0.76 (0.43)	0.73 (0.02)	0.028
Gansu	0.33 (0.03)	0.31 (0.04)	0.023
Henan	0.28 (0.05)	0.49 (0.02)	-0.208***
Shandong	0.38 (0.05)	0.20 (0.03)	0.185***
Perception	0.79 (0.02)	0.63 (0.02)	0.161***
Smartphone use	0.71 (0.05)	0.49 (0.02)	0.214***
Household income	13.56 (0.49)	8.64 (0.39)	4.920***
Observations	351	142	493

Standard errors are in parentheses; *** $p < 0.01$.

Table 4 Determinants of off-farm work and determinants of smartphone use: ESP model estimation

		Smartphone use	
Variable	Off-farm work	Participants	Non-participants
Age	0.098 (0.001)**	0.005 (0.079)	-0.120 (0.194)
Age squared	-0.001 (0.0005)**	-0.001 (0.001)	0.001 (0.002)
Gender	0.486 (0.187)***	0.604 (0.269)**	-0.637 (0.280)**
Education	0.069 (0.029)**	0.020 (0.037)	-0.001 (0.059)
Household size	-0.045 (0.044)	-0.038 (0.066)	0.210 (0.080)***
Vehicle	-0.067 (0.152)	0.180 (0.196)	-0.354 (0.356)
School student	-0.346 (0.180)*	0.135 (0.275)	0.772 (0.341)**
Farm size	-0.020 (0.012)*	0.001 (0.012)	0.067 (0.024)***
Membership	0.238 (0.367)	1.040 (0.525)**	1.944 (0.708)***
Digital camera	0.268 (0.339)	1.302 (0.534)**	2.459 (1.200)**
Road condition	-0.261 (0.170)	0.766 (0.216)***	0.129 (0.336)
Henan	-0.596 (0.175)***	0.859 (0.235)***	0.0152 (0.316)
Shandong	0.370 (0.171)**	0.641 (0.216)***	-0.948 (0.341)***
Perception	0.468 (0.189)**		
Constant	-1.702 (1.186)	1.016 (1.899)	2.351 (4.917)
ρ_1		-0.409 (0.231)*	
ρ_0			-0.870 (0.148)***
Log pseudolikelihood		-440.790	
Wald test of inde. Egns. ($\rho_1 = \rho_0$)		χ^2 (2)=7.39, p=0.025	
Observations	493	493	493

Robust standard errors are in parentheses; *** p<0.01, ** p<0.05, * p<0.1
The reference region is Gansu.

Table 5 Average treatment effects of off-farm work on smartphone use

Category	ATT	*t*-value [a]	ATU	*t*-value [b]
Full sample	0.547***	32.978	0.244***	9.966
Average treatment effects disaggregated by gender				
Male	0.569***	32.512	0.270***	9.629
Female	0.408***	8.947	0.157***	3.329
Average treatment effects disaggregated by survey regions				
Gansu	0.313***	15.353	0.059	1.490
Henan	0.534***	17.600	0.292***	9.167
Shandong	0.763***	40.149	0.415***	8.841

Standard errors in parentheses; *** $p<0.01$

[a] and [b]: *t*-values are calculated based on the immediate form of the *ttest* command in Stata 13.1.

ATT: Average treatment effect on the treated;

ATU: Average treatment effect on the untreated.

Table 6 Impact of off-farm work and smartphone use on household income

Variables	Coefficients	*t*-value
Off-farm work	3.430 (0.753)***	4.56
Smartphone use	2.643 (0.831)***	3.18
Age	1.815 (0.409)***	4.44
Age squared	-0.020 (0.005)***	-3.82
Gender	7.595 (1.689)***	4.50
Education	1.230 (0.270)***	4.55
Household size	-2.208 (0.256)***	-8.64
Vehicle	0.721 (0.769)	0.94
School student	-4.913 (1.332)***	-3.69
Farm size	-0.256 (0.109)**	-2.35
Membership	2.452 (2.436)	1.01
Digital camera	2.966 (2.070)	1.43
Road condition	-1.199 (1.324)	-0.91
Henan	-4.455 (2.035)**	-2.19
Shandong	10.048 (1.384)***	7.26
IMR_off-farm	-4.246 (2.865)	-1.48
IMR_smartphone	26.707 (6.167)***	4.33
Constant	-45.583 (11.305)***	-4.03
Adjusted R^2	0.331	
Test value [a]	F(2, 475)=9.41, p=0.001	
Observations	493	

Robust standard errors are in parentheses; *** p<0.01, ** p<0.05, * p<0.1.
The dependent variable is per capita household income measured in Yuan/1000.
The reference region is Gansu.
[a] H_0: IMR_off-farm= IMR_smartphone=0.

Appendix

Table A1 Impact of off-farm work on smartphone use: RBP model estimation

Variables	Off-farm work (coefficients)	Smartphone use (coefficients)	Smartphone use (marginal effects)
Off-farm work		1.458 (0.271)***	0.526
Age	0.084 (0.050)*	-0.096 (0.089)	-0.034
Age squared	-0.001 (0.0005)*	0.0003 (0.001)	9.89e-05
Gender	0.423 (0.196)**	0.106 (0.205)	0.038
Education	0.066 (0.029)**	0.025 (0.029)	0.009
Household size	-0.035 (0.045)	0.027 (0.046)	0.009
Vehicle	-0.116 (0.158)	0.071 (0.155)	0.025
School student	-0.305 (0.179)*	0.311 (0.196)	0.103
Farm size	-0.018 (0.012)	0.033 (0.012)***	0.012
Membership	0.227 (0.373)	0.943 (0.479)**	0.240
Digital camera	0.272 (0.331)	1.199 (0.506)**	0.276
Road condition	-0.354 (0.185)*	0.507 (0.180)***	0.187
Henan	-0.660 (0.179)***	0.600 (0.182)***	0.199
Shandong	0.292 (0.170)*	0.354 (0.179)**	0.120
Perception	0.567 (0.173)***		
Constant	-1.357 (1.217)	1.834 (2.098)	
ρ'	-0.699 (0.153)***		
Log-likelihood	-462.508		
Wald test: $\rho' = 0$	$\chi^2(1) = 8.339$, p = 0.004		
Observations	493	493	

Robust standard errors are in parentheses; *** p<0.01, ** p<0.05, * p<0.1.
The reference region is Gansu.

Table A2 Join decisions of off-farm work participation and smartphone use: SUBP model estimation

Variables	Off-farm work	Smartphone use
Age	0.104 (0.049)**	-0.048 (0.097)
Age squared	-0.001 (0.0005)***	-0.0004 (0.001)
Gender	0.506 (0.178)***	0.385 (0.197)*
Education	0.091 (0.027)***	0.072 (0.029)**
Household size	-0.042 (0.044)	0.016 (0.049)
Vehicle	-0.079 (0.147)	0.036 (0.168)
School student	-0.308 (0.179)*	0.232 (0.207)
Farm size	-0.020 (0.012)*	0.026 (0.012)**
Membership	0.249 (0.379)	1.183 (0.481)**
Digital camera	0.324 (0.339)	1.557 (0.518)***
Road condition	-0.169 (0.164)	0.484 (0.184)***
Henan	-0.520 (0.173)***	0.405 (0.189)**
Shandong	0.459 (0.172)***	0.577 (0.185)***
Constant	-1.602 (1.185)	1.926 (2.322)
ρ''	0.219 (0.094)**	
Log-likelihood	-451.691	
Wald test: $\rho'' = 0$	$\chi^2(1)$ = 5.099, p = 0.024	
Observations	493	493

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.
The reference region is Gansu.