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Does the application of ICTs facilitate rural economic transformation in China? Empirical evidence from the use of smartphones among farmers

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ABSTRACT

This paper investigates the role of information communication technologies (ICTs) in the transformation of rural economies by evaluating the use of smartphones among farmers in China. We use unique three-wave panel data to document the transformation path of rural economies in recent years. An endogenous switching probit model and a counterfactual analysis are applied to estimate the effects of smartphone use. The results show that from 2008 to 2015, rural economies in China could be characterized by the following three aspects: a) increased off-farm employment, b) expanded grain cultivation, and c) decreased crop diversification. The estimation results indicate that the use of smartphones among farmers had significant impacts on the transformation of rural economies by facilitating the off-farm employment of the farmers' family members, the cultivation of nongrain crops and crop specialization. These findings complement the empirical evidence on the role of ICTs, particularly smartphones, in the development of rural economies in China and other developing countries.

1. Introduction

Information and communication technology (ICT) is one of the most influential technological innovations in the second half of the 20th century and has been considered one of the critical driving forces of social development and economic growth in the 21 st century (G8, 2000; Meng & Li, 2002). Since the 1990s, ICT has been rapidly developed worldwide. In 2000, the 26th summit of the G8 in Japan emphasized the importance of developing ICTs in the 21 st century and identified the essence of ICT-driven economic and social transformation (G8, 2000). Since the 2000s, the rapid development of the ICT sector has fostered economic growth in several developed and developing regional areas.

China plays a significant role in the ICT segment because it has become a major supplier and a fast-growing market in the world; notably, it has the largest population in the world, and its rapid economic development provides enormous demand for ICT-related products and services (Yu, Suojapelto, Hallikas, & Tang, 2008). ICTs, including fixed phones, mobile phones, computers, televisions and the internet, are commonly used in China (Guo & Chen, 2011). By 2016, there were more than 0.73 billion internet users in China, over 95 % of business offices used the internet, and the internet penetration rate was as high as

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53 %. Of these internet users, over 60 % used desktops and nearly 37 % used laptops. Interestingly, approximately 95 % of these internet users connected to the internet using smartphones, and the number of users of smartphones was approximately 690 million (CNNIC, 2017).

Recent government and industrial reports show that ICTs, particularly the mobile internet, are increasingly used in rural China (CNNIC, 2016; DRC, 2017, 2017). As of the end of 2015, the number of rural mobile internet users reached 170 million, increasing by 16.3 % from 146 million in the previous year. Mobile internet users represented approximately 87 % of all internet users, while the proportion of mobile internet users was much higher than that of internet users using desktops (63.4 %) and laptops (25.6 %). Although ICT users in rural China differed in terms of occupation, village membership and social status (Guo & Chen, 2011), recently, they included unlikely users: older adults, rural women, and people with little education or disposable income who were driven by the desire for connection and entertainment (Oreglia, 2014).

In this context, China has attempted to develop a new growth path for the rural economy by integrating the internet and agriculture. While China's agricultural economy has been growing in the past 40 years, the traditional and persistent smallholder farming hinders the development of modern agriculture in China. Thus, the concept of "Internet plus Agriculture" has been developed, and it is highly expected to facilitate the modernization of China's agriculture (DRC, 2017). Specifically, the aim of "Internet plus Agriculture" is to help China's agriculture away from the traditional straits such as information blocking, restricted circulation, farmers' decentralized management, and lagging service systems by relying on the ICTs platform, thereby realizing the transformation from traditional agriculture to modern agriculture. The application of ICTs such as smartphones and internet networks can provide farmers with necessary information services (Aker, 2011; Qiang, Kuek, Dymond, & Esselaar, 2012), which may contribute to improving farmers' capacity and reducing information asymmetry. For instance, as increasing numbers of people use various smartphone applications (apps) in rural China, developing and promoting agriculture-related apps may play a significant role in assisting traditional agricultural extension services (Qiang et al., 2012; Zhang, Duan, & Hu, 2015).

Currently, China's agriculture sector is in a critical period of transforming from traditional to modern agriculture practices, and information processing and dissemination through the efficient deployment of ICTs may play a crucial role in this transformation process (Zhang et al., 2015). The development of ICTs is an essential driver of rural development and has an increasingly significant influence on both economic and social development in China (Chen, Gao, & Tan, 2005). Soriano (2007) suggested that ITCs (proxied by telecenters) have considerable potential for reducing poverty in China through their catalytic role in enhancing rural livelihoods. However, the rapid dissemination of ICTs has widened the gap between people with different levels of ICT exposure due to their different socioeconomic backgrounds (Chu, 2008). Fong (2009) indicated that there was an active correlation in the developing relationship between the Chinese urban-rural income gap and the adoption of ICTs, including the internet, mobile phones, personal computers, and telephones, mainly between 1985 and 2006.

However, to date, few studies have examined the actual application of ICTs in rural China and quantified their impact on the transformation of rural economies. This study takes the use of smartphones among farmers in China as a case. This is due to considering three aspects of smartphones. First, smartphones extend the capabilities of regular mobile phones by providing access to internet-based platforms, further enhancing information flows, e.g., about the weather, jobs, agricultural technology and products, making (financial) transactions easier, and allowing users to review and/or purchase goods or services (Hartje & Hübler, 2017; Hübler & Hartje, 2016; Shin, Shin, Choo, & Beom, 2011). Second, the use of mobile internet through smartphones is the primary choice of internet users in rural China (CNNIC, 2016). Third, although numerous studies have examined the impacts of using mobile phones on agriculture and rural development (e.g., Muto & Yamano, 2009; Aker & Mbiti, 2010; Aker, Clemens, & Ksoll, 2011; Aker, Ksoll, & Lybbert, 2012; Mittal & Mehar, 2012; Urquieta & Alwang, 2012; Zanello, 2012; Lee & Bellemare, 2013; Aker & Fafchamps, 2014; Shimamoto, Yamada, & Gummert, 2015; Tadesse & Bahiigwa, 2015; Aker & Ksoll, 2016), they have not determined whether the use of smartphones can facilitate the transformation of rural economies.

In this study, an endogenous switching probit model is applied to three-wave panel data to account for unobserved factors that could simultaneously affect the use of smartphones and the transformation of farmers' economies. Additionally, a counterfactual analysis is employed to estimate the treatment effects of smartphone use on the transformation of rural economies. The estimation results of our empirical models indicate that the use of smartphones among farmers has significant impacts on the transformation of rural economies by facilitating the off-farm employment of farmers' family members, the cultivation of nongrain crops and crop specialization. The findings of this study imply that strategies for facilitating the transformation of rural economies should take into account the role of internet-based platforms (specifically, smartphones). This study also complements empirical evidence on the impacts of ICTs on the development of rural economies in China and developing countries.

This paper is organized as follows. The next section briefly reviews the existing studies related to the effects of ICTs on agriculture. Section 3 briefly presents the transformation of rural economies in China and the potential impacts of ICTs. Section 4 introduces the methods used to assess the impact of smartphone use on rural economic transformation. Section 5 shows the data source used in this study and the descriptive statistics. Section 6 reports and discusses the estimation results of the empirical models. The last section concludes this study.

2. Literature review

The spread of ICTs worldwide in recent years has attracted much scholarly attention (Chen, Liu, & Song, 2019; Wang & Lin, 2008), while most studies have shown that ICTs have positive impacts on agriculture in developing countries (Aker &

Fafchamps, 2014; Aker & Ksoll, 2012; Aker, Ghosh, & Burrell, 2016; Hübler & Hartje, 2016), which is optimistically called the "Digital Dividend". Aker (2011) reviewed studies on the impacts of ICTs on agriculture and summarized the potential impact mechanisms, such as improving access to information, farmers' learning, and the management of input and output supply chains; reducing transaction costs; and facilitating the delivery of other services, including credit and agriculture and health insurance. Qiang et al. (2012) indicated the application of ICTs in agriculture can stimulate the rapid development of the agricultural sector and rural areas primarily because ICTs can provide millions of farmers with access to information, markets, and services.

In Africa, the strategic use of ICTs by the agricultural sector has positively affected economic growth and poverty alleviation (Chavula, 2014); a study on digital credit through quick small loans offered remotely over digital channels showed that ICTs are increasingly used in sub-Saharan Africa (Hwang & Tellez, 2016). Chavula (2014) used 2000–2001 panel data for 34 African countries and found that ICTs played a significant role in enhancing agricultural production. Although mobile technologies are widely used, mobile phones have a nonsignificant impact on agricultural production, while main telephone lines remain a significant contributor to agricultural growth.

In Asia, Kaushik and Singh (2004) claimed that the use of ICTs could contribute to broad economic development in North India and that ICTs could also benefit the poor by providing better access to education or government services. Drawing upon survey data from rural Southeast Asian households, Hartje and Hübler (2017) found that smartphone ownership could increase labor mobility (measured as the number of commuters), while Hübler and Hartje (2016) found a significant and positive impact of smartphone and mobile phone ownership on household income. Therefore, these authors believed that advanced mobile communication devices could support rural economic development.

However, the impacts of ICTs on the equity of agricultural and economic development are ambiguous. Based on data for 81 countries from 1995 to 2000, Lio and Liu (2006) found that the level of ICTs was much higher in wealthier countries than in poorer countries and that the returns from ICTs used for agricultural production in wealthier countries were also approximately two times higher than the returns in poorer countries. In addition, the authors noted that ICTs lead to a divergence between countries regarding overall agricultural productivity. In contrast, Meng and Li (2002) argued that the global diffusion of ICTs could help developing countries reduce the economic gap between developing and developed countries. However, Deichmann, Goyal, and Mishra (2016) pointed that although there were many promising examples of the positive impacts of ICTs on rural livelihoods, they have not scaled up to the extent expected because technology can address only some of the barriers faced by farmers in poorer countries.

While China plays a significant role in the sector of ICTs globally, empirical evidence on the role of ICTs in the agriculture of rural development in China is lacking. Exceptions include the studies conducted by Ma, Grafton, and Renwick (2018); Ma, Renwick, Nie, Tang, and Cai (2018); Leng, Ma, Tang, and Zhu (2020); Ma, Nie, Zhang, and Renwick (2020), and Nie, Ma, and Sousa-Poza (2020). The former three studies revealed the positive impacts of smartphone use on farmers' farm income, off-farm income, income diversity in rural China, respectively. The study of Ma et al. (2020) investigated the positive impact of internet use on economic well-being of rural households, while Nie et al. (2020) found that smartphone use could improve subjective well-being in rural China. However, these studies did not explore the development trend of smartphone use among farmers or the potential impact of smartphone use on farmers' farming and nonfarming behaviors. Hence, more empirical studies assessing the possible impact of ICTs on rural economies in China are needed.

3. Conceptual framework

Since China launched its economic reforms in the late 1970s, China's economic transformation underwent dramatic and continuing structural changes (Chen, Jefferson, & Zhang, 2011). Notably, the transformation of rural economies significantly raised farmers' incomes and massively reduced rural poverty (Huang & Yang, 2017; Zhi, Huang, Huang, Rozelle, & Mason, 2013). The main feasures of the transformation include changes in agricultural structure, growth in agriculture, and increased off-farm employment (Huang & Ding, 2016; Huang & Yang, 2017). According to previous studies, the driving factors of rural economic transformation in China comprise institutional innovation (Deininger, Jin, Xia, & Huang, 2014; Huang & Ding, 2016; Huang & Rozelle, 1996; Lin, 1992a), technology change (Fan & Pardey, 1997; Huang & Rozelle, 1996; Lin, 1992b), market reform (de Brauw, Huang, & Rozelle, 2004; Huang & Yang, 2017), and investment in agriculture (Babu, Huang, Venkatesh, & Zhang, 2015; Huang & Rozelle, 2014; Huang, Yang, & Rozelle, 2010).

As a kind of technological innovation, ICTs has been widely applied in rural China in recent years. According to prvious studies, farmers' decisions to use ICTs such as smartphone just like a kind of technological choice, and therefore are influenced by the characteristics of the household head, household, and farm (Leng et al., 2020; Ma, Grafton et al., 2018). Theoretically, younger and higher educated farmers are more likely accept new technology and thereby have a higher probability to use ICTs (Leng et al., 2020). The impacts of gender and farm size on the use of ICTs are ambiguous and appear to depend on sample features, according to the mixed results from previous studies (Ma, Grafton et al., 2018; Ma, Renwick et al., 2018). The study of Ma, Grafton et al. (2018) showed that for the household heads without participating off-farm employment, only female and owning more land tend to use smartphones. Due to the potential differences in social cognition, language and wealth between the Han majority and the minorities, they may also have heterogeneous decisions on smartphone use. As smartphone can be used to communication between working adults and left-behind children and elders, household population structure may also influence the decision of smartphone use (Leng et al., 2020).

The application of ICTs may facilitate the transformation of rural economies (Fadiji & Omokore, 2010) and help to bridge the development divide (Sreekumar, 2005). Referring previous studies (Parvathi, Nguyen, Grote, & Waibel, 2018; Parvathi, Amare, Nguyen, & Barrett, 2019), agricultural structure such as crop diversity (Oehmke et al., 2017), and off-farm employment (Barrett, Christian, & Shiferaw, 2017) are important indicators measuring rural economic transformation. To assess the impact of ICTs on rural economic transformation, here we particularly focus on the use of ICTs by farmers, agricultural structure of their households, and off-farm employment of their family members.

The role of ICTs in the transformation of rural economies may include the following potential mechanisms. First, the use of ICTs can help farmers access to job market information and enhance their communication with left-behind family members (Jensen, 2007; Hartje & Hübler, 2017; Ma, Grafton et al., 2018). Thereby, the use of ICTs by farmers may support their off-farm employments (Hartje & Hübler, 2017). Second, the use of ICTs by farmers can affect allocation of input factors (e.g. land and labor) by facilitating farmers' access to agricultural information, social network, and communications between farmers and input/output dealers (Aker & Fafchamps, 2014; Aker & Ksoll, 2016; Aker, 2010; Alam & Mamun, 2017; Benedict, 2010; Ma, Grafton et al., 2018; Ogutu, Okello, & Otieno, 2014). In return, the use of ICTs is supposed to be correlated with crop diversification (Oehmke et al., 2017) and land allocation for cash crops (Leng et al., 2020).

4. Model specification

To estimate the impact of smartphone use on the transformation of rural economies in China, we must consider that this use may be subject to endogeneity. First, the endogeneity may be due to the causality issue. There may exist reverse relationships between smartphone use and the three indicators of rural economic transformation. Second, the endogeneity may be resulted by sample selection bias arising from the fact that farmers who use smartphones may have systematically different characteristics from the farmers that did not use smartphones (Di Falco, Veronesi, & Yesuf, 2011). Moreover, unobserved heterogeneity of farmers may affect both the use of smartphones and the transformation of rural economies, resulting in inconsistent estimates of the impact of smartphone use on the three indicators of rural economic transformation.

Following previous studies, the endogenous switching probit model (ESP) can well addressed above issues (Ayuya et al., 2015; Gregory & Coleman-Jensen, 2013; Manda et al., 2016; Min, Waibel, & Huang, 2017; Parvathi & Nguyen, 2018). The ESP model takes into account unobserved household characteristics that could simultaneously affect households' decisions to use smartphones and to participate in off-farm work or to transform agricultural structures (Lokshin & Glinskaya, 2009). The full information maximum likelihood method can be used to simultaneously estimate the functions of these two decisions to yield consistent standard errors of the estimates (Lokshin & Sajaia, 2011). In addition to estimating an ESP model, a counterfactual analysis is conducted to derive the average treatment effect of smartphone use (Di Falco & Veronesi, 2013; Lokshin & Sajaia, 2011).

4.1. ESP regression

We assume that in a rural household, a family member's decision to use a smartphone like a kind of technological choice and is determined by the characteristics of the entire household. Following the setting of the ESP model used by Lokshin and Glinskaya (2009), a household's propensity to use smartphones (at least one smartphone) can be expressed in a linearized form as

$$M_i^* = \gamma Z_i + \mu_i \tag{1}$$

where subscript i denotes the household; Z_i is a vector of independent variables including the characteristics of the household head, household, farm and village; γ is a vector of parameters to be estimated, and μ_i is an error term. Thus, the observed status of smartphones used in households (M_i) can be written as

$$M_i = 1[M_i^* \geq 0] = 1[\gamma Z_i + \mu_i \geq 0] \tag{2}$$

where $1[\cdot]$ is an indicator function, denoting $M_i = 1$ if $M_i^* \geq 0$; otherwise, $M_i = 0$.

The proposed three indicators of rural economic transformation discussed in the last section are assumed to be expressed as

$$h_{imj} = \beta_{mj} X_i + v_{imj} \quad (\mathrm{m} = 1, 2, 3;\ \ \mathrm{j} = 0, 1) \tag{3}$$

where the subscript m denotes the three indicators: h_{i1j} represents the propensity of a household having at least one family member engaged in off-farm work, h_{i2j} denotes a household's propensity to plant nongrain crops, and h_{i3j} indicates the propensity of a household to diversify the types of crops planted (plant more than 5 types of crops). The subscript j denotes the two regimes (use smartphones/do not use smartphones), while β_{mj} is a regime-specific vector of parameters. X_i is a vector of the characteristics of the household head, household, farm, and village; v_{imj} is the regime-specific error term. Following the specification of the three observed indicators of rural economic transformation discussed in the last section, the observed transformation status of the household can be written as

$$R_{imj} = 1[h_{imj} \geq 0] = 1\left[\beta_{mj}X_i + v_{imj} \geq 0\right] \quad (\mathrm{m} = 1,2,3;\ \mathrm{j} = 0,1) \tag{4}$$

where $1[\cdot]$ is an indicator function. $R_{i1j} = 1$ represents a household with at least one family member participating in off-farm work, $R_{i2j} = 1$ denotes a household that plants nongrain crops, and $R_{i3j} = 1$ indicates a household engaged in relatively high crop diversification (planting more than 5 types of crops)[1] .

Following Lokshin and Glinskaya (2009), the error terms $(\mu_i, v_{im0},\ v_{im1})$ in Eqs. (2) and (4) are assumed to be jointly normally distributed with a zero-mean vector and the following correlation matrix:

$$\Omega_{\mathrm{m}} = \begin{pmatrix} 1 & \rho_{m\mu 0} & \rho_{m\mu 1} \\ & 1 & \rho_{m01} \\ & & 1 \end{pmatrix} \tag{5}$$

where the terms $\rho_{m\mu 0}$ and $\rho_{m\mu 1}$ are the correlations between v_{m0}, v_{m1}, and μ; ρ_{m01} is the correlation between v_{m0} and v_{m1}. Because R_{im1} and R_{im0} are never observed simultaneously, the joint distribution of $(v_{m0},\ v_{m1})$ is not identified, and ρ_{m01} cannot be estimated. Following Lokshin and Sajaia (2011), we assume that $\rho_{m01} = 1$ (γ is estimable only up to a scalar factor). This model can be identified by the nonlinearities of its functional form. According to Lokshin and Glinskaya (2009), the log-likelihood functions for the three simultaneous systems of Eqs. (2) and (4) can be expressed as

$$\begin{aligned} \ln(\xi) = & \sum_{M_i \neq 0;\ R_{im} \neq 0} \ln\left\{\Phi_2\left(\beta_{m1}X_i,\ \gamma Z_i, \rho_{m\mu 1}\right)\right\} + \sum_{M_i \neq 0;\ R_{im} = 0} \ln\left\{\Phi_2\left(-\beta_{m1}X_i,\ \gamma Z_i, -\rho_{m\mu 1}\right)\right\} \\ & + \sum_{M_i = 0;\ R_{im} \neq 0} \ln\left\{\Phi_2\left(\beta_{m0}X_i, -\ \gamma Z_i, -\rho_{m\mu 0}\right)\right\} + \sum_{M_i = 0;\ R_{im} = 0} \ln\left\{\Phi_2\left(-\beta_{m0}X_i,\ \ -\gamma Z_i, \rho_{m\mu 0}\right)\right\} \end{aligned} \tag{6}$$

where Φ_2 is the cumulative function of a bivariate normal distribution. The function (6) can be estimated by the full information maximum likelihood method (Lokshin & Sajaia, 2011).

4.2. Average treatment effect

The advantage of using the ESP model specified in Eq. (6) is that it can derive the probabilities of a counterfactual case, such as determining the economic transformation of a household that uses smartphones (Ayuya et al., 2015). Following the methodological framework developed by Aakvik, Heckman, and Vytlacil (2000) and the empirical specification presented by Lokshin and Glinskaya (2009) and Lokshin and Sajaia (2011), the impact of smartphone use on the probability of economic transformation for the household randomly drawn from the households with characteristics x can be expressed as a treatment effect (TE) as

$$\mathrm{TE}(x) = \Pr[R_m = 1|X = x] - \Pr[R_m = 0|X = x] \tag{7}$$

Then, the average treatment effect (ATE) can be further obtained from Eq. (7) by averaging TE(x) for the sample of households that use smartphones ($N_{M=1}$):

$$\mathrm{ATE} = \frac{1}{N_{M=1}} \sum_{M=1} \mathrm{TE}(x_i) \tag{8}$$

The ATE for a subgroup of the whole sample households can be derived as the average TE(x) for that subgroup (Gregory & Coleman-Jensen, 2013; Lokshin & Sajaia, 2011); for example, the ATE for the households belonging to the Han ethnicity can be written as

$$\mathrm{ATE}_{\mathrm{Han}} = \frac{1}{n_k} \sum_{i=1}^{n_k} \mathrm{TE}(x_i) \tag{9}$$

where n_k is the number of Han households with smartphones.

4.3. Identification strategy and key variables

To estimate the established ESP model, at least one instrumental variable should be included in the adoption equation of smartphone. Following previous studies, Eq.s (2) and (4) are characterized by nonlinearity even if the variables in X and Z entirely overlap (Lokshin & Glinskaya, 2009). It is vital for the Z variables in the adoption model (Eq. 2) to contain a selection instrument (Manda et al., 2016). Additionally, for the model to be robust, we need exclusion restrictions. Following previous studies (e.g., Di Falco et al., 2011; Ma & Abdulai, 2016; Manda et al., 2016; Min et al., 2017; Parvathi & Nguyen, 2018), the inclusion of variables as exclusion restrictions can be validated using a falsification test. According to this test, a variable is

[1] A robustness check in the appendix further reports the estimate results which make use of continuous variables of crop diversification.

used as a selection instrument if it affects the use of smartphones but does not affect the economic transformation of rural households that do not use smartphones.

We employ "The broadband penetration rate in a county" as an instrumental variable for the identification of the impact of smartphone use. Intuitively, the broadband penetration rate in a county can reflect the development circumstance of broadband internet in local, which may affect the use of smartphones among farmers in the county, i.e., if the circumstance of broadband internet is more developed in a county, a rural household living there is more likely to use smartphones. Meanwhile, the proposed IV does not have a direct effect on the household's economic transformation; instead, this variable has an indirect impact on the household's economic transformation by affecting the use of smartphones. Finally, a falsification test is used to further check for the exogenous restriction and validate the proposed IV; the results in Table A3 confirm the validity of the proposed IV empirically.

5. Data and descriptive statistics

The data used in this study were obtained from four waves of a household survey conducted in rural China by the China Center of Agricultural Policy, Peking University (CCAP). The first wave data were collected from a randomly selected sample of 1147 households from 58 villages in 6 provinces (including Shaanxi, Zhejiang, Sichuan, Hubei, Liaoning, and Hebei) in rural China that were selected to represent all of China's major agricultural regions in 2008. This dataset is called the 2008 China National Rural Survey (or 2008 CNRS dataset) and has been widely used in previous studies (Huang, Wang, Zhi, Huang, & Rozelle, 2011, b, Wang, Huang, Zhang, & Rozelle, 2011; Huang, Gao, & Rozelle, 2012; Huang, Wang, & Rozelle, 2013; Gao, Huang, & Rozelle, 2012; de Brauw, Huang, Zhang, & Rozelle, 2013; Zhi et al., 2013; Deininger et al., 2014). The second wave of the household survey was conducted at the end of 2013 to follow the sample households of the 2008 CNRS dataset. Accordingly, a total of 1067 households were successfully surveyed, and we established a 2008&2013 CNRS panel dataset. Due to a change in the research focus, the third-wave household survey conducted in 2016 updated the sample households by adding some new sample households; this wave included only 50 % of the households in four provinces, including Shaanxi, Zhejiang, Sichuan, and Hubei, which were also included in the 2008 & 2013 CNRS panel dataset. Consequently, a panel dataset (2008 & 2013 & 2015) including 342 households from 4 provinces in China was compiled. Unfortunately, the detailed information of ICTs was not included in the three wave surveys.

To assess the ICTs and the development of e-commerce in rural China, a complementary survey of the samples that the CCAP surveyed in 2016 was carried out in April-May 2017. This survey further collected historical information regarding ICTs such as access to the internet, the possession and use of smartphones, and the use of e-commerce for agricultural production and sales. Additionally, the village heads were interviewed to collect information on the infrastructure of ICTs in the village in the past years. These data on ICTs, including smartphones, were further combined with the panel dataset (2008 & 2013 & 2015) at the household level according to household code and year, thereby forming the panel dataset of ICT application in rural China that was employed in this study. However, due to the existence of some mismatching samples between the ICT-related data and the panel dataset (2008 & 2013 & 2015) and missing data for some of the variables used in the analysis, finally, this study used a balance panel dataset (2008 & 2013 & 2015) with 232 households. The total number of observations is 696. Table A1 in the Appendix presents the distributions of these sample households by province, county and village.

5.1. The indicators of rural economic transformation in China

To measure the transformation of rural economies in China, we use three indicators referring previous studies (Barrett et al., 2017; Oehmke et al., 2017; Parvathi et al., 2018) as mentioned in Section 3. First, "off-farm employment" indicates whether any family members in a household participate in off-farm work. As long as one family member participates in off-farm work, we will treat "off-farm employment" equaling 1, otherwise 0. As shown in Table 1, approximately 66.4 % of households had at least one family member participating in off-farm work in 2008. This percentage was 89.7 % by 2013 and 85.3 % by 2015. A mean-comparison test suggests that the percentage of households with family members participating in off-farm work in 2013 and 2015 is significantly higher than that in 2008, while there is no significant difference in the

Table 1
The three indicators of rural economic transformation by year.

Year	Obs.	Off-farm employment		Nongrain crop cultivation		Crop diversification	
		Freq.	Percent (%)	Freq.	Percent (%)	Freq.	Percent (%)
All	696	560	80.5	480	69.0	255	36.6
2008	232	154	66.4	175	75.4	127	54.7
2013	232	208	89.7	176	75.9	56	24.1
2015	232	198	85.3	129	55.6	72	31.0
Diff. (2013−2008)			23.3***		0.6		−30.6***
Diff. (2015−2008)			18.9***		−19.8***		−23.7***
Diff. (2015−2013)			−4.4		−20.3***		6.9*

Note: Mean-comparison test, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.Source: Authors' survey.

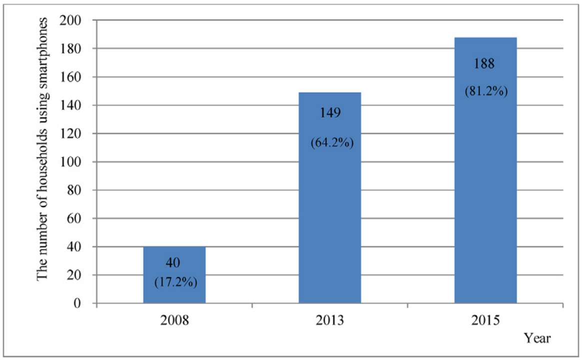

Fig. 1. The use of smartphones among sample households.

percentages between 2013 and 2015. Hence, the overall trend of off-farm employment increased from 2008 to 2015, which is mainly derived by the large surplus labor in rural and the increasing wages and is consistent with the findings for the previous periods (de Brauw, Huang, Rozelle, Zhang, & Zhang, 2002; Wang et al., 2011; Wang, Huang, & Rozelle, 2017; de Brauw et al., 2013; Li, Huang, Luo, & Liu, 2013).

Second, "Nongrain crop cultivation" indicates "whether a household planted nongrain crops". Although the area shares of nongrain crops increased from 20 % in 1978 to 32 % in 2014 (Huang & Yang, 2017), Table 1 shows that from 2008 to 2015, decreasing numbers of farmers allocated their land for nongrain crop cultivation. Specifically, the percentage of farmers planting nongrain crops decreased from approximately 75 % in 2008 to 56 % in 2015. This is resulted by the implementation of grain direct subsidy policies and grain minimum purchase price policy, which motivates farmers to plant more grain crops.

Third, "crop diversification" indicates "the number of the types of crops planted by a household". Wang et al. (2017) used the third indicator to reflect agricultural specialization. The survey results indicate that the average number of types of crops planted by a household declined from approximately 6.58 in 2008 to 3.86 in 2015. However, the third indicator suffers from a problem of under-dispersion because its mean (4.70) is larger than its variance (4.05). To simplify the following econometric analysis, similar to the first and second indicators, we dichotomize the dummy variable "Crop diversification" by using its median value "5" as a cut-off point (1=Plant more than five crops; 0=Otherwise). Accordingly, as shown in the last column of Table 1, the overall trend is that decreasing numbers of farmers have diversified the types of crops they plant (planted more than five types of crops), although the percentage of farmers planting more than five types of crops in 2015 was slightly higher than that in 2013. This result is reasonable due to the increasing agricultural specialization (Wang et al., 2017); the latter contributes more to improving agricultural productivity than crop diversification.

5.2. The use of smartphones and its correlation with the rural economic transformation

Fig. 1 shows an increasing trend in the number of households using smartphones[2] from 2008 to 2015. Specifically, 40 households used smartphones in 2008, representing approximately 17.2 % of the sample households. By 2013, the number and proportion of households using smartphones increased to 149 and 64.2 %, respectively, and continued to increase to 188 and 81 %, respectively, by 2015. Overall, the use of smartphones has significantly and rapidly increased in rural China since 2008; more than 80 % of sample households possessed at least one smartphone by 2015.

Table 2 shows the differences between the three indicators used for rural economic transformation between households for households that do and do not use smartphone. First, of the households using smartphones, 88.3 % had at least one family member engaged in off-farm work, which was significantly higher than that for households that did not use smartphones. Second, approximately 75 % of the households using smartphones planted nongrain crops, while only approximately 64 % of households that did not use smartphones planted nongrain crops. Third, compared to households that did not use smartphones, a significantly smaller proportion of households using smartphones planted more than five crops. Hence, the use of smartphones among farmers seems to foster the transformation of rural economies toward increased off-farm employment, increased nongrain crop cultivation and decreased crop diversification.

5.3. Descriptive statistics of key variables

The detailed definitions and statistics of all variables used in the regression are summarized in Table 3. Referring previous studies regarding the impacts of ICTs or smartphone use in rural China (Leng et al., 2020; Ma, Grafton et al., 2018), the independent variables include the characteristics of the household head, household, and farm. The definitions and descriptions of all variables are provided in column 2, while columns 3–5 present the mean values of all variables for 2008,

[2] Here, the smartphones also include the early Symbian-based smartphones.

Table 2
The difference between the three indicators of rural economic transformation between households that do and do not use smartphones.

Indicators of rural economic transformation	Smartphone use status		Diff.(Yes-No)
	Yes	No	
Off-farm employment (%)	88.3	71.2	17.1***
Nongrain cultivation (%)	74.6	64.2	10.4***
Crop diversification (%)	31.0	43.3	−12.3***

Note: Mean-comparison test, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.Source: Authors' survey.

Table 3
Summary and description of key variables.

Variables	Definition and description	2008	2013	2015	Difference (2013−2008)	Difference (2015−2008)	Difference (2015−2013)
Household heads							
Gender	Gender of the household head (1=Male; 0=Female)	0.948	0.927	0.935	−0.022	−0.013	0.009
Age	Age of the household head	52.129	56.267	58.457	4.138***	6.328***	2.190**
Edu	Education of the household head (in years)	6.616	6.440	6.610	−0.177	−0.006	0.170
Ethnic	Ethnicity of the household head (1=Han; 0=Minorities)	0.940	0.940	0.940	0.000	0.000	0.000
Households and farms							
Hhsize	The number of family members	3.970	4.328	4.401	0.358***	0.431***	0.073
Child	The proportion of children (Age<16 years old) in the household	0.121	0.129	0.124	0.008	0.003	−0.005
Elder	The proportion of elders (Age≥ 60 years old) in the household	0.151	0.229	0.230	0.078***	0.079***	0.000
Farm	Farm size of the household (mu/person)	1.766	2.053	1.744	0.287	−0.023	−0.309
Penetration	Broadband penetration rate in a county	0.366	0.827	0.918	0.461***	0.552***	0.091***
Observations		232	232	232			

Note: Mean-comparison test, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.Source: Authors' survey

2013 and 2015, respectively. Additionally, the remaining three columns report the differences in the mean values of all variables between 2013 and 2008, 2015 and 2018, and 2015 and 2013. The results show that in contrast to the age of the household head, the number of family members and the proportion of elders in the household, the mean values of other variables for 2013 and 2015 are not significantly different from those for 2008. There are no significant differences in the mean values for 2015 and 2013 for the age of the household head. The instrumental variable used in this study is the broadband penetration rate in a county, which significantly increased from 36.6 % in 2008 to 91.8 % in 2015. As we control for the fixed effects at the village level, here, all potential explanatory variables at the village level are omitted.

The statistical results shown in Table A2 indicate that there are possible correlations between the key variables and the use of smartphones, off-farm employment, nongrain crop cultivation, and crop diversification. For instance, columns 2–4 in Table A2 show that there is a significant difference in the mean values of the variables for the age and gender of the household between the households that do and do not use smartphones. This result indicates that a household has a higher probability of smartphone use if the household head is female and older. Some other variables are also correlated with the three indicators of rural economic transformation to varying degrees.

6. Empirical results

6.1. Estimation results

Table 4 presents the results of the ESP regressions for off-farm employment, the cultivation of nongrain crops, and crop diversification, controlling for the fixed effects of village and year. At the bottom of these three tables, the results of the Wald chi^2 tests are shown, and they are always significantly different from zero, suggesting that the specifications of the three empirical models are statistically valid. Also, the chi^2 test (rho1=rho2 = 0) results show the joint dependence of the equations for smartphones and employment, the equations for smartphones and nongrain cultivation, and the equations for smartphones and crop diversification. However, most Rho1/0 are significantly different from zero, indicating the existence of selection bias which will skew the effect of smartphone use on off-farm employment, nongrain crop cultivation, and crop diversification.

For the selective equation for the use of smartphones, the estimation results of three models are almost same and hence only one of which is reported in the first column of Table 4. As we expected, the penetration ratio of broadband internet in the

Table 4
ESP regressions for off-farm employment, nongrain cultivation, and crop diversifications.

Variables	Smartphone use#	Off-farm employment		Nongrain cultivation		Crop diversification	
		Smartphone use = 1	Smartphone use = 0	Smartphone use = 1	Smartphone use = 0	Smartphone use = 1	Smartphone use = 0
Penetration	0.552**						
	(0.230)						
Gender	−0.859***	0.583	0.716	−0.035	1.103***	1.239***	0.498
	(0.272)	(0.488)	(0.445)	(0.544)	(0.404)	(0.317)	(0.364)
Age	−0.006	0.001	−0.040***	0.009	0.002	−0.001	0.002
	(0.009)	(0.012)	(0.014)	(0.011)	(0.011)	(0.009)	(0.009)
Edu	0.004	−0.013	0.033	−0.060	−0.011	−0.010	0.014
	(0.021)	(0.026)	(0.029)	(0.044)	(0.030)	(0.023)	(0.021)
Ethnic	−0.641	3.361***	2.700***	0.578	−0.146	0.253	−0.401
	(0.458)	(0.880)	(0.661)	(0.734)	(0.571)	(0.768)	(0.505)
HHsize	0.132***	0.285***	0.161*	0.231***	0.203**	0.080	0.228***
	(0.050)	(0.062)	(0.092)	(0.083)	(0.092)	(0.056)	(0.067)
Child	−0.305	0.074	−1.023	−0.723	0.693	−0.061	−0.329
	(0.481)	(0.749)	(0.708)	(0.793)	(0.626)	(0.604)	(0.574)
Elder	−0.149	−1.308***	−0.442	0.600	0.274	−0.093	−0.424
	(0.289)	(0.442)	(0.379)	(0.682)	(0.370)	(0.329)	(0.303)
Farm	0.024	0.021	−0.135**	0.145*	0.425***	−0.007	0.190***
	(0.024)	(0.014)	(0.060)	(0.085)	(0.076)	(0.013)	(0.066)
2013	1.275***	2.034***	0.721**	0.031	−0.778***	0.190	−1.615***
	(0.183)	(0.321)	(0.298)	(1.018)	(0.211)	(0.275)	(0.191)
2015	1.808***	2.347***	−0.444*	−0.673	−1.615***	0.726**	−1.713***
	(0.198)	(0.302)	(0.254)	(1.498)	(0.277)	(0.289)	(0.249)
Village fixed effect	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
_cons	−0.171	−6.194***	−2.257*	−2.450	−1.451*	0.372	−1.877*
	(0.829)	(0.857)	(1.201)	(1.686)	(0.861)	(1.117)	(0.967)
Rho1/0		10.333*	−9.478***	0.564	−8.641***	−7.310***	8.757**
		(5.515)	(2.227)	(1.223)	(1.830)	(1.764)	(4.231)
N		696		696		696	
Log-likelihood		−486.01		−531.77		−619.50	
Wald Chi2		2626.14***		245.52***		2064.75***	
Chi2 (rho1=rho0 = 0)		21.63***		22.36***		23.94***	

The estimation results for smartphone use almost the same among these three models, here we just report one of them; Robust standard errors are in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.0$.

located county significantly and positively affect the use of smartphone among farmers. Thus, promoting the development of broadband internet in rural may have a positively external effect on fostering the use of smartphones among farmers. In addition, the gender of the household head and household size in the household also significantly affect the use of smartphones. These results reveal that a household with a female household head and larger household size is more likely to use smartphones. However, the variables such as age and education are not significant and fully different with the results of previous studies (e.g. Ma, Grafton et al., 2018). This may be resulted by two aspects: 1) this study only focuses on the household heads in our samples; 2) we controlled for the fixed effects of village and year, while previous studies rarely controlled for this level. Thus, the variations of the characteristics of household heads in a village in much smaller than those of samples used in previous studies. Thereby, it is not surprised that the significances of some characteristic variables in this study may be not consistent with those in previous studies. Finally, the significant and positive coefficients for the year dummy variables also confirm that since 2008, smartphones have been spreading at a remarkable pace in rural China.

In the model for the off-farm employment of household members, for households using smartphones (column 3), the independent variables such as ethnicity, household size and the proportion of elders in the household were significantly associated with the off-farm employment of family members. This result illustrates the interactive effects of the use of smartphones and these independent variables on the decision to engage in off-farm work. Additionally, the age of the household head, ethnicity, household size and farm size significantly affect the off-farm employment of family members for households that did not use smartphones (column 4). Regardless of whether the households use smartphones, Han ethnic farmers are always more likely to engage in off-farm employment, while the number of family members is also always positively associated with the probability of engaging in off-farm employment. The other significant variables differ for households that did and those that did not use smartphones.

The heterogeneity of the variables that show a significant difference between the households that did and did not use smartphones appears in the models of nongrain crop cultivation and crop diversification to varying degrees. As shown in columns 5-6, the gender of a household head has different impacts on the household's land use for nongrain crop cultivation between households using smartphones and those not using smartphones, while the variables regarding household size and farm size always positively affect the decision to plant nongrain crops. In the model for crop diversification (columns 7–8), a household has a higher probability of crop diversification if the household uses smartphones and the household head is male. Household size and farm size positively affect the likelihood of crop diversification for households that did not use smartphones.

6.2. The ATEs of smartphone use and observable household characteristics

Based on the estimation results of the ESP models (Table 4) and Eqs 7–9, we conduct a counterfactual analysis to simulate the impact of smartphone use on the transformation of rural economies. As shown in the first row of Table 5, the results of the ATE show that the impact of smartphone use on off-farm employment, nongrain crop cultivation, and crop diversification of a household randomly selected from the whole sample of households is 8.8 %, 3.8 %, and -12.4 %, respectively. The use of smartphones has fostered farmers' off-farm employment (Hartje & Hübler, 2017), nongrain crop cultivation (Aker & Ksoll, 2016), and agricultural specialization.

The simulated ATEs have some observable characteristics, as shown in Table 5, and reveal the heterogeneity of the effect of smartphone use on the transformation of rural economies. First, the ATEs vary for the characteristics of the household head. The ATEs of smartphone use on off-farm employment and nongrain crop cultivation for households with female household heads are larger than those with male household heads. However, the ATE of smartphone use on crop diversification for female household heads is not significant. The positive ATEs on both off-farm employment and nongrain cultivation are for households whose household heads are 60 years old and older. There exist heterogenous ATEs of smartphone use on all three indicators of rural economic transformation among different age groups of the household head. The ATEs of smartphone use on off-farm employment for minority ethnic households are larger than those for the Han ethnic households, but the ATE on nongrain cultivation is negative for minority ethnic households.

Second, the ATEs of the characteristics of households on smartphone use are also different. The households with more family members have the strongest ATEs on all three indicators of rural economic transformation. Similarly, the ATEs of

Table 5
ATEs of smartphone use and household characteristics.

Variables	ATEs of off-farm employment	ATEs of nongrain cultivation	ATEs of crop diversification
All samples	0.088**	0.038***	−0.124***
Gender			
a. Male	0.076*	0.029**	−0.140***
b. Female	0.254***	0.173***	0.099
Diff.(b-a)	0.178***	0.144**	0.239***
Age			
a. Age<40	−0.199***	−0.069	−0.416***
b. 40 ≤ Age<60	0.031	−0.001	−0.167***
c. Age≥60	0.219***	0.114***	−0.014
Diff.(b-a)	0.230***	0.068	−0.249***
Diff.(c-a)	0.418***	0.183**	−0.402***
Education			
a. Edu≤6 years	0.174***	0.085***	−0.107*
b. 6 < Edu≤9	0.012	0.003	−0.124***
c. Edu≥10	−0.023	−0.041	−0.189***
Diff.(b-a)	−0.162***	−0.082***	−0.017
Diff.(c-a)	−0.131***	−0.126*	−0.081
Ethnicity			
a. Han	0.078**	0.049***	−0.129***
b. Others	0.240**	−0.133**	−0.052
Diff.(b-a)	0.112*	−0.182***	0.077
Household size			
a. HHsize<5	0.047*	0.002	−0.235***
b. HHsize≥5	0.148***	0.091***	0.038
Diff.(b-a)	0.101***	0.089***	0.273***
Child			
a. Yes	0.123***	0.071***	−0.033
b. No	0.056***	0.009	−0.207***
Diff.(b-a)	−0.067**	−0.062**	−0.174***
Elder			
a. Yes	0.147***	0.096***	−0.041*
b. No	0.030	−0.018	−0.205***
Diff.(b-a)	−0.116***	−0.114***	−0.164**
Farm size			
a. 1st quantile	0.168***	0.149***	0.005
b. 2nd quantile	0.034	0.042**	−0.158***
c. 3rd quantile	0.061**	−0.077***	−0.222***
Diff.(b-a)	−0.134***	−0.107*	−0.163**
Diff.(c-a)	−0.107**	−0.226***	−0.227**

smartphone use on off-farm employment and nongrain crop cultivation are strongest for households with more children or those with elders. For households with a small farm (1 st quantile), the ATEs of smartphone use on off-farm employment and nongrain crop cultivation are the largest, but the ATE of smartphone use on crop diversification is not significant.

Finally, to ensure that the main results of this study are not driven by the model specifications, we carry out a series of robustness checks using alternative models. First, we use an alternative instrumental variable "Broadband" i.e. accessibility to broadband internet in a county (1=Yes; 0=No) for the identification of smartphone use. Second, we further add more control variables that may be correlated with the transformation of rural economies but that were omitted in the main models due to endogeneity problems. In the third alternative model, the dependent variables for off-farm employment, nongrain crop cultivation, and crop diversification are converted to the corresponding continuous forms, considering that the forms set for the dependent variables may affect the estimation results. As shown in the section of robustness check and Tables A4–A7 in appendix, although there are somewhat differences in the impact extents of smartphone use on three indicators of rural economic transformation, these results consistently confirm the robustness of the main findings of this study.

7. Concluding remarks

The use of smartphones, which is one of the main applications of ICTs, has been extensively spreading in China, even in rural regions. Relative to regular mobile phones, smartphones enhance various information flows by extending access to internet-based platforms and thereby may affect farmers' behaviors. This study examined the possible effects of ICTs on economic transformation in rural China by evaluating the use of smartphones among farmers. We used three-wave panel data from 4 provinces and applied an ESP regression model to analyze the use of smartphones among farmers and their impacts on the three proposed indicators of rural economic transformation in China.

Our findings show that from 2008 to 2015, the transformation of rural economies in China involved an increase in off-farm employment, grain cultivation and agricultural specialization. Since 2008, the use of smartphones among farmers has been spreading, such that over 80 % of the sample households used smartphones in 2015. Furthermore, farmers are more likely to use smartphones if there is a relatively high broadband penetration rate in a county. A female household head, more family members, and larger farm size foster the use of smartphones in a household.

The main finding is that the use of smartphones had a significant impact on the transformation of rural economies in three regards by facilitating the off-farm employment of family members, nongrain crop cultivation, and agricultural specialization. However, considering the relatively high popularity of smartphones among farmers, the further promotion of smartphones may be limited. Hence, strategies for facilitating the transformation of rural economies in the future should take into account the role of smartphones and consider providing more apps for farmers using smartphones with internet-based platforms. Furthermore, the findings of this study to some extent support the concept of “Internet plus Agriculture”. We would like to recommend the government to design and promote more specific measures regarding “Internet plus Agriculture”, such as “Internet plus employment services”, “Internet plus agricultural market information”, and “Internet plus farm management”, which may play a substantial role in promoting rural economic transformation.

Finally, we would like to point out the main limitations of this study. First, this study just focused on the first-level digital divide- smartphone use participation instead of second-level digital divide (smartphone use intensity) and even third-level digital divides (specific activities within smartphone use). Second-level and third level digital divides may have more policy implications. Therefore, a comprehensive analysis is needed urgently in future studies. Second, in essence, the data cover four provinces in China, so that the conclusions are quite difficult to generalize to the whole China; meanwhile, external validity is also a concern. Thus, future studies should employ a more representative sample, which could have broader implications for rural China. Third, while this study finds some influences of smartphone use on rural economic transformation, underlying mechanisms through which smartphone use operates on these three aspects remain untouched and deserve more attention in future study. Finally, the effects of ICTs or smartphone use on the transformation of rural economies may not only be explored in economics but also sociology, implying the importance to conduct interdisciplinary works.

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Appendix A

Robustness check

To check the robustness of the main findings in this study, we carried out the following three procedures. First, we use an alternative instrumental variable "Broadband" i.e. accessibility to broadband in the county (1=Yes; 0=No) for the identification of the impact of smartphone use. This instrumental variable is also validated by a falsification test. The reestimation results of the ESP models by using the new instrumental variable suggest the ATEs of smartphone use on off-farm employment, nongrain crop cultivation, and crop diversification are 0.093, 0.059, and -0.125, respectively. While the magnitudes of these impacts are different from the findings in the main body of this study, their directions are the same with those. Hence, the findings that smartphone use has a significant impact on the transformation of rural economies in three regards by facilitating the off-farm employment of family members, nongrain crop cultivation, and agricultural specialization are robust (Table A3).

Second, we further add more control variables that may be correlated with the transformation of rural economies but that were omitted in the main models due to endogeneity problems. As smartphones combine the communication function of regular phones and the internet function of computers, regular phones and computers are alternatives to smartphones to some extent. Considering that regular phones are almost universal in our sample, we further control for a variable measuring the use of computers to estimate the empirical models of off-farm employment, nongrain cultivation, and crop diversification. Accordingly, 12.22 %, 37.78 % and 50 % of the sample households used computers in 2008, 2013 and 2015, respectively. The results of the first alternative specification suggest that the use of smartphones positively affects the off-farm employment of family members and nongrain cultivation but negatively impacts crop diversification (the re-estimated results will be provided upon request). This result is consistent with the main findings of this study. However, the ATEs of smartphone use on the three indicators of rural economic transformation decline slightly after controlling for the variable of using computers, 0.037, 0.134 and -0.058, respectively.

In the third alternative model, the dependent variables for off-farm employment, nongrain crop cultivation, and crop diversification are converted to the corresponding continuous forms, considering that the forms set for the dependent variables may affect the estimation results. Our final specification continues using the endogenous switching regressions to address the potential endogeneity of the use of smartphones in explaining the transformation of rural economies. Nevertheless, the outcome equations of a probit form could be replaced by linear or Poisson forms. Table A4 reports the results of the third alternative specification. Because the estimation of an endogenous switching model sometimes cannot be realized due to a problem regarding nonconcavity, the family members' off-farm employment and nongrain crop cultivation are estimated by using the endogenous switching regression (ESR), while crop diversification is estimated by using the endogenous switching Poisson regression (ES-Poisson). The estimation results are presented in Tables A5–A7 of the appendix. As shown in Table A4, the simulated results for the ATE and ME of smartphone use confirm the main findings of this study, i.e., the use of smartphones indeed fosters China's rural economic transformation by facilitating farmers' off-farm employment, nongrain cultivation and agricultural specialization. The estimation results of the continuous variables of the three indicators of rural economic transformation are in line with our main findings. Hence, the estimation results are robust to the third alternative specification .

Table A1
Sample distribution of the panel data used in this study (completely traced households without missing data).

Province	Number of sample counties	Number of sample townships (villages)	Number of sample households
Shaanxi	5	10	80
Zhejiang	5	10	49
Sichuan	4	8	42
Hubei	5	10	61
Total	19	38	232

Source: Authors' survey

Table A2
Descriptive statistics of the correlations between the key variables and the three indicators.

Variables	Smartphone			Off-farm employment			Nongrain cultivation			Crop diversification		
	Yes	No	Diff.(Y-N)	Yes	No	Diff.(Y-N)	Yes	No	Diff.(Y-N)	Yes	No	Diff.(Y-N)
Gender	0.918	0.959	−0.041**	0.939	0.926	0.013	0.958	0.889	0.069***	0.961	0.923	0.038**
Age	56.660	54.385	2.275***	54.729	59.279	−4.550***	55.517	55.843	−0.326	54.698	56.150	−1.452*
Edu	6.688	6.398	0.290	6.787	5.603	1.184***	6.387	6.931	−0.544*	6.786	6.422	0.364
Ethnic	0.939	0.940	−0.001	0.939	0.941	−0.002	0.933	0.953	−0.020	0.929	0.945	−0.016
Hhsize	4.491	3.928	0.563	4.455	3.316	1.139***	4.296	4.093	0.203	4.318	4.184	0.134
Child	0.131	0.116	0.015	0.135	0.084	0.051***	0.129	0.115	0.014	0.126	0.124	0.002
Elder	0.197	0.210	−0.013	0.157	0.395	−0.238***	0.204	0.202	0.002	0.170	0.223	−0.053**
Farm	1.867	1.840	0.027	1.718	2.415	−0.697**	2.057	1.404	0.653**	2.065	1.733	0.332
Obs.	377	319		560	136		480	216		255	441	

Note: Mean-comparison test, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.Source: Authors' survey.

Table A3
Falsification test for the validity of the proposed IV for smartphone use.

Variables	Smartphone	For households that do not use smartphones		
		Off-farm employment	Nongrain cultivation	Crop diversification
Penetration	0.508**	0.403	0.468	−0.238
	(0.195)	(0.578)	(0.604)	(0.546)
Other variables	Controlled	Controlled	Controlled	Controlled
Year fixed effect	Controlled	Controlled	Controlled	Controlled
Village fixed effect	Controlled	Controlled	Controlled	Controlled
_cons	−1.440***	−2.095	−0.733	−3.038***
	(0.588)	(1.421)	(1.323)	(1.100)
N	696	294[a]	228[b]	296[c]
Pseudo R^2	0.265	0.424	0.381	0.276
Log likelihood	−353.04	−105.27	−87.86	−146.43
Chi-squared	430.37***	143.14***	91.95***	109.27***

Note: Robust standard errors are in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; [a] 25 observations were not used due to the success of perfectly predicting during the regression; [b] 9 (82) observations were not used due to the failure (success) of making perfect predictions during the regression; [c] 12 (11) observations were not used due to the failure (success) of making perfect predictions during the regression.

Table A4
The impacts of smartphone use on the number of family members participating in off-farm work, the proportion of nongrain crop cultivation in the total planting area, and the number of types of planted crops.

Categories	Off-farm employment (Number of family members participating in off-farm work)	Nongrain cultivation (Proportion of nongrain crop cultivation in the total planting area)	Crop diversification (Number of types of planted crops)
ESR	Yes	Yes	Nonconcave
ATEs of smartphone use	0.58***	0.12***	
ES-Poisson	Nonconcave	Not applicable	Yes
ME of smartphone use			−1.13***

Note: $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A5
ESR for the number of family members participating in off-farm work.

Variables	Smartphone	No. of family members participating in off-farm work	
		Smartphone = 1	Smartphone = 0
Broadband	0.420**		
	(0.157)		
Gender	−0.767***	−0.168	0.143
	(0.278)	(0.218)	(0.318)
Age	−0.007	−0.020***	0.001
	(0.009)	(0.007)	(0.007)
Edu	0.005	0.020	0.054***
	(0.022)	(0.017)	(0.017)
Ethnic	−0.553	0.728**	−0.372
	(0.455)	(0.332)	(0.452)
HHsize	0.141**	0.289***	0.412***
	(0.068)	(0.063)	(0.059)
Child	−0.517	−1.848***	−1.741***
	(0.582)	(0.376)	(0.424)
Elder	−0.221	−0.506**	−1.062***
	(0.285)	(0.235)	(0.274)
Farm	0.028	−0.068	0.002
	(0.018)	(0.056)	(0.010)
Year fixed effect	Controlled	Controlled	Controlled
Village fixed effect	Controlled	Controlled	Controlled
_cons	0.201	1.921***	1.703*
	(0.714)	(0.708)	(0.996)
Rho1/0		0.381	0.068
		(1.004)	(0.224)
N		696	
Log- likelihood		−1183.05	
Wald Chi2		349.63***	
Chi2 (rho1=rho0 = 0)		0.29	

Note: Robust standard errors are in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A6
ESR for the proportion of nongrain cultivation in the total planting area.

Variables	Smartphone	Proportion of nongrain cultivation	
		Smartphone = 1	Smartphone = 0
Broadband	0.355*		
	(0.177)		
Gender	−0.781***	0.040	0.085
	(0.275)	(0.075)	(0.105)
Age	−0.007	−0.0002	0.003
	(0.009)	(0.002)	(0.002)
Edu	0.003	−0.013*	−0.003
	(0.021)	(0.007)	(0.006)
Ethnic	−0.541	0.077	0.071
	(0.453)	(0.124)	(0.08)
HHsize	0.133**	0.030**	0.008
	(0.052)	(0.015)	(0.017)
Child	−0.459	−0.178	0.325***
	(0.496)	(0.151)	(0.121)
Elder	−0.229	0.128	−0.096
	(0.312)	(0.085)	(0.073)
Farm	0.027*	0.008***	0.036***
	(0.016)	(0.003)	(0.008)
Year fixed effect	Controlled	Controlled	Controlled
Village fixed effect	Controlled	Controlled	Controlled
_cons	0.209	0.210	1.882**
	(0.260)	(0.394)	(0.902)
Rho1/0		0.093	−0.178
		(0.423)	(0.552)
N		696	
Log-likelihood		−414.51	
Wald Chi2		1372.30***	
Chi2 (rho1=rho0 = 0)		0.14	

Note: Robust standard errors are in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A7
Endogenous switching Poisson regression for the number of types of planted crops.

Variables	Smartphone		Number of types of planted crops
Broadband	0.392*		
	(0.211)		
Smartphone			−0.927***
			(0.175)
Gender	−0.658**		0.761***
	(0.264)		(0.173)
Age	−0.002		0.006
	(0.008)		(0.005)
Edu	0.008		−0.015
	(0.020)		(0.012)
Ethnic	−0.420		−0.144
	(0.410)		(0.257)
HHsize	0.137***		0.046
	(0.052)		(0.030)
Child	−0.182		0.123
	(0.507)		(0.289)
Elder	−0.353		0.145
	(0.272)		(0.162)
Farm	0.091***		0.027***
	(0.034)		(0.010)
Year fixed effect	Controlled		Controlled
Village fixed effect	Controlled		Controlled
_cons	−0.849		0.372
	(0.779)		(1.117)
Rho			0.012
			(0.473)
N		696	
Log-likelihood		−2033.47	
Wald Chi2		295.03***	

Note: Robust standard errors are in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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