Received: 9 May 2022 | Revised: 10 May 2022 | Accepted: 17 May 2022

DOI: 10.1111/agec.12728

AGRICULTURAL ECONOMICS
The Journal of the International Association of Agricultural Economists
IAAE
WILEY

ORIGINAL ARTICLE

Facilitating inclusive ICT application and e-Commerce development in rural China

Jikun Huang | **Lanlan Su** | **Qiwang Huang** | **Xinyu Liu**

China Center for Agricultural Policy, School of Advanced Agricultural Sciences, Peking University, Beijing, P.R. China

Correspondence
Jikun Huang, Lanlan Su China Center for Agricultural Policy, School of Advanced Agricultural Sciences, Peking University, Beijing, P.R. China.
Email: jkhuang.ccap@pku.edu.cn; lanlansu.ccap@pku.edu.cn

Funding information
National Natural Science Foundation of China, Grant/Award Number: 71934003; National Social Science Foundation of China, Grant/Award Number: 19ZDA002; Alibaba Group, Grant/Award Number: JLA50WBJ1210043

Abstract
Application of information and communication technologies (ICTs) in general and e-commerce development in particular are increasingly becoming one of the important driving forces of transforming rural economy in China. Based on two sets of household survey datasets in 2015–2019, this study documents the overall trends of major ICTs' and e-commerce adoption in rural China and farmers' selling fruits online in more developed e-commerce villages in two provinces, and examines the enabling and constraining factors for farmers adopting ICTs and using e-commerce to sell products. The results show that, although the increase has been impressive, there is still plenty of room for the diffusion of ICTs and e-commerce. Empirical analyses suggest that human capital, social networks, resource endowments, ICT infrastructure and location are the main determinants of a household's or an individual's adoption of ICTs, and the producer's selling his/her fruits through e-commerce. Moreover, this study provides new and strong evidence of intergenerational support for older and less educated farmers from their children to engage in online sales. However, this study also points out that a new digital divide on the spread of ICTs and e-commerce has emerged across regions and among farmers in rural China. The article concludes with several policy implications for fostering rapid and inclusive ICT application and e-commerce development in rural areas in the coming digital era.

KEYWORDS
digital divide, e-commerce, ICTs, inclusiveness, rural China

JEL CLASSIFICATION
D10, O12, Q12

1 | INTRODUCTION

Information and communication technologies (ICTs) have spread globally, but there is large gap between the developed and developing countries. According to the International Telecommunication Union (ITU, 2018), it is estimated that about 58% of households had internet access at home, almost half of all households had at least one computer and 76% of the population owned at least one mobile phone globally in 2018. However, the percentages of households with internet access (85%), computer (83%) and individuals owning a mobile phone (92%) in the developed countries were much higher than the corresponding numbers (47% for internet access, 36% for a computer, and 73% for a mobile phone) in the developing countries (ITU, 2018). In the developing countries, there is also a

AGRICULTURAL ECONOMICS The Journal of the International Association of Agricultural Economists IAAE

large gap in ICT's spread between rural and urban areas (Deichmann et al., 2016; Nakasone et al., 2014).

China has also experienced a rapid expansion of ICTs and has made great efforts to reduce the gap between rural and urban areas since the early 2000s. Nationally, the penetration rate of internet increased from 16% in 2007 to 70% in 2020; the number of internet users increased from 210 million to 989 million, and mobile phone subscriptions rose from 50 million to 986 million over the same period (China Internet Network Information Center or CNNIC, 2021). In 2007, the rural internet penetration rate was only 7%, much lower than the 26% rate in urban areas. By 2020, while the internet penetration rate in urban areas (80%) was about three times that of 2007, it increased eightfold in rural areas (to 56%). Facilitating rural ICT development was first included in the National Economic and Social Development Five-Year Plan, released in 2001. Since then, the central and local governments have sustained investment in rural ICT infrastructure, the provision of broadband, capacity building and training, and policy support for rural e-commerce (the Ministry of Agriculture & Rural Affairs, 2020).

Driven by the significant increase in the internet penetration, e-commerce has also developed rapidly in China. For example, the value of online sales in rural areas rose from 353 billion yuan in 2015–1,800 billion yuan in 2020, accounting for about 15% of the national online retail value in 2020 (Ministry of Commerce, 2021). In terms of agricultural products, online retail reached 398 billion yuan in 2019. Moreover, Taobao Villages, which started in 2009, reached 5425 in 2020 (Ali Research, 2020). Although the share of Taobao Villages was less than 1% of China's 690,000 villages, their rapid growth means that this share is expected to increase significantly in the future.

There has been an increasing number of empirical studies on adoption of ICTs and e-commerce by rural households across the world. These show that human capital, household resources (e.g., access to land and credit, etc.) and local ICT infrastructure are major factors affecting farmers' adoption of ICTs (e.g., Aker & Mbiti,2010; Enoch et al., 2014; Ma et al., 2018) and e-commerce (e.g., Li et al., 2021; Liu et al., 2021). Emerging studies have provided empirical evidence for the economic welfare of engaging in e-commerce on rural households in terms of income, especially operating income (Luo & Niu, 2019; Zeng et al., 2018) and sales prices (Li et al., 2021). However, there are also concerns about the potential inequality due to the uneven spread of ICTs (e.g., Guo & Chen, 2011; Hartje & Hübler, 2017; Leng et al., 2020) and e-commerce (e.g., Liu et al., 2020; Luo & Niu, 2019) across and within regions.

The overall goal of this study is to further examine the major factors affecting rural household's adoption of ICTs and e-commerce in China. While this is similar to many existing studies, we contribute to the literature in three areas. First, we use unique datasets on ICT adoption from primary household surveys with national representative samples in rural China in 2015–2019. Second, in addition to provide new evidence of major factors affecting farmers' selling their agricultural products through e-commerce discussed above, we find a pathway for older and less educated farmers to break barriers in using e-commerce through their children who have nonfarm work with a wide social network connection. Last but not the least, we pay particular attention to the inequality engendered by ICT and e-commerce adoption across regions and among rural households within the same village. The results of this study should have important policy implications for fostering inclusive adoption of ICTs and e-commerce in not only China but also other developing countries.

The rest of this article is organized as follows: Section 2 introduces the household survey datasets and documents the development trends of major ICTs and e-commerce in rural China. Section 3 describes the main factors that likely affect the adoption of ICTs and e-commerce. Section 4 discusses the empirical models and estimation strategies used in this study. Section 5 presents the estimation results. The last section concludes this study with several policy implications.

2 | DATA

Two sets of household survey data used in this study are from the national representative surveys (Dataset 1) and e-commerce survey (Dataset 2), both conducted by the authors. Dataset 1 is used to present the overall trends in ICT and e-commerce use by rural households in 10 provinces surveyed from 2015 to 2019 and to examine enabling or constraining factors affecting farmers' use of ICTs over the same period. Because rural households selling their products online was still only in its infancy (about 2%) in 2019 based on Dataset 1, we conducted a further survey in more advanced e-commerce counties in Zhejiang and Shandong provinces (Dataset 2) and used this to examine enabling or constraining factors affecting farmers' uses of e-commence in 2015–2019.

2.1 | Dataset 1: The national representative surveys

2.1.1 | Sampling approach

To have better samples representing rural households in major agricultural production regions in China, we combine three stratified random household surveys in 10 provinces (Datasets 1a, 1b, and 1c) to form a national representative sample (Dataset 1). Dataset 1a covers the surveys in Zhejiang, Hubei, Guangdong, Shaanxi, Sichuan and Jiangxi with data from 2015 to 2019; Dataset 1b comes from the surveys in Liaoning and Hebei provinces with data also from 2015 to 2019; and Dataset 1c includes the surveys in Henan and Shandong with data in 2015 and 2016. The location of each surveyed county in each of 10 provinces is presented in Map 1.

For Datasets 1a and 1b, the same stratified random sampling approach is applied. In each of these 8 provinces, all counties were arranged in descending order of gross value of industrial output (GVIO) per capita, and then divided evenly into five groups in all provinces except Jiangxi with 12 groups due to more research funding from this province. One county was randomly selected from each group (12 counties in Jiangxi and five counties in each of other seven provinces). The same procedure was also applied to select two townships from each county except the counties from Jiangxi (three townships per county) based on GVIO per capita. In each sampled township, one administrative village was randomly selected. Within each village, 20 households (or 10 households in Jiangxi) were randomly selected. A total sample of 2480 households ($1,400 = 20 \times 1 \times 2 \times 5 \times 7$ in the seven provinces and $1,080 = 10 \times 3 \times 3 \times 12$ in Jiangxi province) was selected for survey. The first wave of survey was conducted in early 2017 with data for 2015 and 2016; the second wave for the same households was conducted in the end of 2019 with data for 2017–2019. This procedure resulted in a final sample of 2526 households (1451 in the seven provinces and 1075 in Jiangxi province) because some new households were added in 2019 in place of households from the 2017 round which could not be followed up in 2019.

Dataset 1c from Henan and Shandong also used a stratified random sampling approach but based on the area of cultivated farmland per capita. We ranked all counties in descending order of area of cultivated land per capita in each county within a province, and then divided evenly into three groups and one county randomly selected from each group. In each selected county two townships and then two villages per township were selected using the same procedures. Then, 10 households were randomly selected from each village. A total of 240 households ($10 \times 2 \times 2 \times 3 \times 2$) were surveyed in 2017 for data in 2015 and 2016, and only one household did not complete the survey.

In all surveys, face-to-face interviews were conducted for each village and each household. The survey mainly collected information on demographics, internet access, use of computers and smartphones, agricultural production and marketing. Additionally, village leaders were interviewed to collect information on the ICT infrastructure in the village.

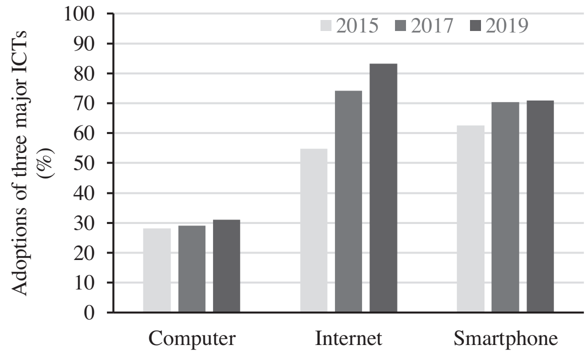

FIGURE 1 Adoptions of three major ICTs by rural households or individuals in 2015-2019. *Source*: Authors' own surveys

Because the surveyed samples differ among provinces, particularly between Jiangxi and the other seven provinces and over time due to using both follow-up samples and additional new samples, it is necessary to have a sample weight system for generating whole sample mean and regression analysis. The sample weights at the household level, were based on the number of households surveyed in each year in each province, while at the individual level the sample weights were calculated based on the number of individuals surveyed in each year in each province.

2.1.2 | The adoptions of major ICTs by rural households and individuals

Rural households deploy ICT mainly in the form of access to the internet, having computer in the household, and owning a smartphone by individuals. Figure 1 shows the adoption of three major ICTs in rural China from 2015 to 2019 based on Dataset 1. Among the three indicators, the share of households with internet access increased faster than the share with a computer, and individuals with a smartphone. By 2019, the percentage of households with a computer and access to the internet reached 30% and 83%, respectively, while the percentage of individuals with a smartphone reached 71%. These results are consistent with the data for whole population as reported by CNNIC (2021).

Figure 2 shows the adoption of these three major ICTs by province in 2015–2019. While the adoption rates have increased in nearly all provinces, the level of adoption differs between the provinces for computer and internet, but not for the percentage of individuals using smartphones.

The share of rural households with a computer and access to the internet has increased over time but not at the same rate in the different provinces. For example, less than

AGRICULTURAL ECONOMICS
The Journal of the International Association of Agricultural Economists
IAAE

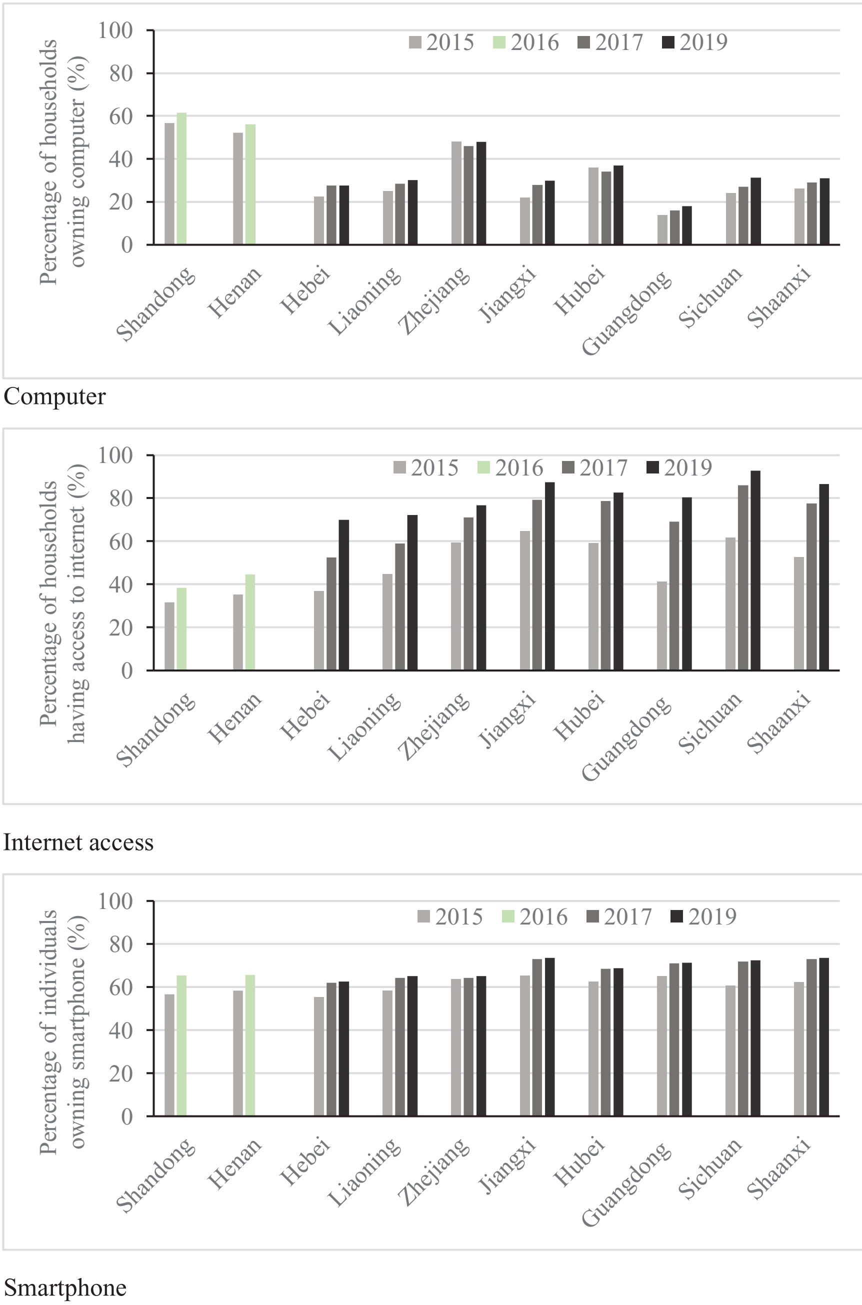

FIGURE 2 The adoptions of three major ICTs by provinces in rural China, 2015–2019. *Source*: Authors' surveys

one third of rural households had a computer in Hebei, Liaoning, Jiangxi, Guangdong, Sichuan and Shaanxi by 2019, leaving a lot of room for expansion. The data shows that the penetration rate of internet access in all surveyed provinces was close to or more than 70% in 2019. Growth rates in Hebei, Guangdong and Liaoning provinces were higher than the other sampled provinces.

Despite its rapid development, our survey data show that e-commerce is still not a common marketing channel for farmers. In 2015, fewer than 1% of farmers had sold their products online, and by 2019, this proportion was still only about 2%. When we asked farmers what the most important reason was, about two thirds said they lacked the necessary e-commerce skills, while some 30% lacked the appropriate storage facilities, and the remainder included the lack of packing and marketing skills and the high logistics costs.

2.2 | Dataset 2: E-commerce survey in Zhejiang and Shandong provinces

2.2.1 | Sampling approach

Considering that only about 2% of rural households sold their products online by 2019 in our national

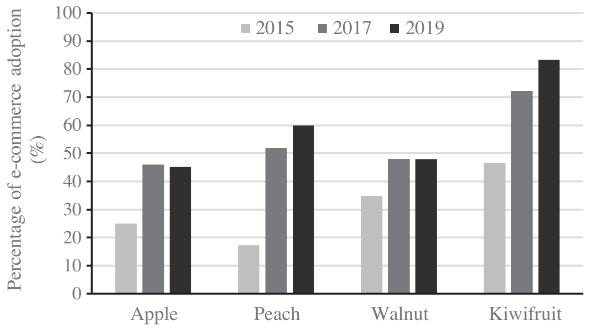

FIGURE 3 The percentage of households selling their fruits online in the selected villages in Shandong and Zhejiang in 2015–2019. *Source*: Authors' surveys

representative rural household surveys, we conducted a special rural e-commerce survey on fruits. Fruits (apple, peach, walnut and kiwifruit) were selected because they are more likely to be sold online than bulk commodities such as grain and edible crops that often need processing. For this sample, we selected counties that produce these fruits and have experienced more advanced e-commerce development, namely Qixia county for apples and Feicheng county for peaches in Shandong province, Linan county in Zhejiang province for walnuts, and Suichang and Jiangshan counties in Zhejiang for kiwifruit (see the blue dots in Map 1). Four villages producing the studied fruits with e-commerce were selected for each of apples, peaches and kiwifruit. For walnuts, the samples were expanded to 6 villages. In each of the sampled villages we aimed to randomly select 10–15 households based on the size of the villages. Finally, we selected 225 households for the first round of the survey (for data in 2015–2017), conducted in the early 2018. In the second round of the survey in early 2020 we were able to follow up only 198 households but added 45 new households to have a total sample of 243. Consequently, we construct an unbalanced panel dataset with total observations of 1090 in 2015–2019 (205 to 230 observations for each year).

2.2.2 | Selling fruits by e-commerce

Figure 3 presents the trends of rural households engaging in agricultural e-commerce from 2015 to 2019. Overall, the farmers have increasingly used e-commerce to sell their fruit in our studied villages. Specifically, the proportions of farmers using e-commerce to sell apples, peaches, walnuts and kiwifruit were 25%, 17%, 35%, and 47%, respectively, in 2015; these proportions increased to 45%, 60%, 48%, and 83% in 2019. Statistics of samples also show that the proportions of apples, peaches, walnuts and kiwifruit sold through online channels (e.g., WeChat, Taobao and other platforms) were 8%, 11%, 29%, and 33%, respectively, in 2015, increasing to 19%, 26%, 34%, and 40% in 2019. This suggests that, even though the sales of these four kinds of fruits are still dominated by offline channels (e.g., wholesale and local retail), the online sales have increased significantly.

3 | VARIABLES AND DESCRIPTIVE STATISTICS

In general, two sets of variables reflecting the characteristics of individuals, households and villages are used to explore the major factors that may affect farmers' ICTs adoption and e-commerce participation. The definitions of all variables are shown in the Table 1.

3.1 | Explanatory variables for ICTs adoption

Through comparing the official statistics and our data presented in Tables 2 and 3, we confirm that our samples are well representative of the national statistics in rural China. These include average household head's age, gender, education, farm land and household size (National Bureau of Statistics of China or NBSC, 2020). Furthermore, official statistics show that the proportion of rural laborers with a nonfarm job was 41.5% in 2019, while the proportion in our sample was 42% (Table 3). On the other hand, our surveyed villages seem have better infrastructure than the country as a whole. Nearly 20% of the sampled villages had at least one business office established by the China Mobile, China Unicom or China Telecom, the three major providers of mobile communication services in rural China. More importantly, the surveyed villages had universal coverage of mobile phone services and broad-band internet since 2016.

Table 2 shows the descriptive results of ICT adoption at the household level. Generally, there are significant differences in the observed characteristics between adopters and nonadopters of computers and the internet. On average, those household heads adopting computers and the internet are younger, with more years of schooling, and have work experience in the nonfarm economy. Also, households with more family members, especially members engaging in nonagricultural jobs and cultivating more farmland, show a higher propensity to adopt ICTs. Moreover, village infrastructure and neighborhood ICT adoption is positively correlated with the households' adoption of computers and the internet.

Table 3 shows the differences in the characteristics between smartphone adopters and nonadopters.

AGRICULTURAL ECONOMICS
The Journal of the International Association of Agricultural Economists
IAAE

TABLE 1 Definitions of all variables used in this study

Variables	Definition
Panel A: Variables for ICTs adoption	
ICTs adoption	
Computer	1 if the household has a computer, 0 otherwise
Internet	1 if the household can access to internet, 0 otherwise
Smartphone	1 if the individual with age > = 16 years old has a smartphone, 0 otherwise
Household head or individual characteristics	
Age	Age of household head or individual (year)
Education	Years of education (year)
Gender	1 if male, 0 otherwise
Nonfarm	1 if engaged in a non-farm job, 0 otherwise
Household characteristics	
Others_nonfarm	Number of household members engaged in nonfarm jobs excluding the household head or certain individual with age ≥16 years old
Farmland	Area of cultivated land of the household (hectare)
Household size	Number of the household members
Village characteristics	
Neighbor computer	Percentage of other sampled households owning computers in the same village (%)
Neighbor internet	Percentage of other sampled households accessing to internet in the same village (%)
Neighbor smartphone	Percentage of other sampled individuals with age > = 16 years old owning smartphones in the same village (%)
Telecom	1 if there has at least one business office established by the China Mobile or China Unicom or China Telecom in the village, 0 otherwise
Panel B: Variables for E-commerce adoption	
E-commerce	1 if the fruits producer sells apples, peaches, walnuts or kiwifruit online
Individual characteristics	
Age	Age of the sale decision-maker (year)
Education	Years of education of the sale decision-maker (year)
Gender	1 if the sale decision-maker is male, 0 otherwise
Train	1 if the sale decision-maker participated in e-commerce training, 0 otherwise
Smartphone	1 if the sale decision-maker has a smartphone, 0 otherwise
Nonfarm	1 if the sale decision-maker engages in nonfarm job, 0 otherwise
Household characteristics	
Others_nonfarm	Number of members engage in nonfarm jobs excluding the sale decision-maker
Farmland	Area of cultivated land of the household (hectare)
Cooperation	1 if the household is a member of farmer's professional cooperative, 0 otherwise
Relative	Number of the household's relatives (within 3 generations) with marketing business
Village characteristics	
Express	1 if the village has a post office, 0 otherwise

(Continues)

TABLE 1 (Continued)

Variables	Definition
Distance	Distance from the village to the nearest agricultural market (kilometer)
Interaction	
Child	1 if any child of the sale decision maker engages in a job with a high level of social network connection that can contact many people through using ICTs,[a] 0 otherwise

[a]The persons who have the jobs with high level of social network connection are defined as those who work as public official, professional staff or technician, businessman, wholesaler, retailer or logistics practitioner.

TABLE 2 Descriptive statistics of the computer and internet adoption at the household level

		Computer (Mean = .28, Std. Dev. = .45)			Internet (Mean = .74, Std. Dev. = .44)		
Variables	**Mean**	**Yes**	**No**	**T-test**	**Yes**	**No**	***t*-Test**
Household head characteristics							
Age	56.28	53.08	57.53	−4.45***	54.82	60.56	−5.74***
Education	6.79	7.86	6.37	1.49***	7.10	5.85	1.25***
Gender	.98	.99	.98	.01***	.99	.97	.02***
Nonfarm	.30	.44	.25	.19***	.36	.12	.24***
Household characteristics							
Others_nonfarm	.92	.95	.61	.34***	.93	.35	.58***
Farmland	.33	.37	.29	.08***	.35	.30	.05*
Household size	4.25	4.27	3.58	.69***	4.86	3.29	1.57***
Village characteristics							
Neighbor computer	31.01	43.25	25.66	17.59***	32.03	26.35	5.68***
Neighbor internet	75.78	79.56	74.17	5.39***	81.04	60.01	21.03***
Neighbor smartphone	68.72	71.92	66.82	5.10***	70.12	62.77	7.35***
Telecom	.20	.23	.18	.05***	.20	.18	.02

Note: Observations = 13,570. *, **, and *** indicate $p < .10$, $p < .05$, $p < .01$, respectively.

TABLE 3 Descriptive statistics of the smartphone adoption at the individual level

		Smartphone (Mean = .70, Std. Dev. = .46)		
Variables	**Mean**	**Yes**	**No**	**T-test**
Individual characteristics				
Age	45.62	39.55	59.77	−20.22***
Education	7.55	8.67	4.92	3.75***
Gender	.52	.55	.46	.09***
Nonfarm	.42	.56	.09	.47***
Household characteristics				
Others_nonfarm	.92	1.06	.59	.47***
Farmland	.33	.34	.31	.03***
Household size	4.25	4.36	4.00	.36***
Village characteristics				
Neighbor computer	31.01	32.27	28.06	4.21***
Neighbor internet	75.78	77.49	71.79	5.70***
Neighbor smartphone	68.72	70.65	64.21	6.44***
Telecom	.20	.21	.18	.03

Note: Observations = 45,933. *, **, and *** indicate $p < .10$, $p < .05$, $p < .01$, respectively.

AGRICULTURAL ECONOMICS
The Journal of the International Association of Agricultural Economists
IAAE
WILEY

TABLE 4 Descriptive statistics of the e-commerce adoption

Variables	Mean	E-commerce (Mean = .49, Std. Dev. = .50) Yes	No	*t*-Test
Decision-maker characteristics				
Age	48.46	45.19	51.64	−6.45***
Education	9.39	10.19	8.62	1.57***
Gender	.84	.80	.88	−.08***
Train	.31	.50	.14	.36***
Smartphone	.83	.95	.71	.24***
Nonfarm	.49	.61	.39	.22***
Household characteristics				
Others_nonfarm	1.01	1.15	.87	.29***
Farmland	.53	.72	.35	.37***
Cooperation	.30	.40	.21	.19***
Relative	1.82	2.14	1.51	.63***
Village characteristics				
Express	.18	.22	.12	.10***
Distance	8.27	7.01	9.49	−2.48***
Interaction				
Child	.20	.23	.18	.05**

Note: Observations = 1090. *, **, and *** indicate $p < .10$, $p < .05$, $p < .01$, respectively.

Similar to those findings in Table 2, there exist significant differences in all of the characteristics except Telecom between smartphone adopters and nonadopters. Specifically, the individuals with smartphones are younger, better educated and more frequently employed in nonfarm sectors than those without a smartphone. Meanwhile, the individuals with larger families, especially members engaging in nonfarm jobs, and more land, also tend to have a smartphone. Moreover, the neighborhood effect is a potential enabling factor for individual's usage of smartphones.

Table A1 in the Appendix shows more details of the relationships between the three major ICT applications and the characteristics of individuals, households and villages. The results also raise concerns about the inequality that could arise from ICTs adoption in rural areas.

3.2 | Explanatory variables for fruit producers using e-commerce to sell their products

Table 4 shows the detailed statistics of all variables used in the estimation of the propensity of fruit producers to use e-commerce to sell their products, with nearly half of fruit producers (49%) engaged in e-commerce in 2015–2019. The results show that decision makers who are younger and female with more years of schooling, training in e-commerce and the smartphone, and with a nonfarm job tend to be more likely to use e-commerce to sell their fruit. The same is true where there are more family members working in a nonfarm job, where the household has more farmland, is a member of a farmer cooperative, and has more relatives (within three generations) working in agricultural business. Moreover, the condition of local logistical infrastructure and locations also contributes to the differences in fruit producers' propensity to sell their fruit online.

The survey results confirm the importance of intergenerational support from the decision maker's children. Specifically, the children of decision-makers, in particular those with old age and little schooling, often act as the actual operator in doing business online. To measure this effect, we constructed a variable named "Child" (see the note to Table 1). The analysis (shown in the last row of Table 4) indicates that approximately 20% of the decision-makers had at least one child engaging in a job with a high level of social network connection. As expected, fruit producers using e-commerce to sell their fruits have a higher percentage of children working in the above job (23%) than households not using e-commerce (18%).

Table A2 in the Appendix presents the percentage of fruit producers using e-commerce by different levels of each variable for individual, household and village characteristics. The results further confirm the descriptive analyses presented in Table 4.

4 | MODEL SPECIFICATION AND ESTIMATION

Following a common approach on a household's or individual's decision on whether to adopt new technology, we posit that the decision depends on the utility the household or individual expects to derive. The adoption occurs when the expected utility of using $ICTs(U_{1i})$ is greater than the utility without using ICTs (U_{0i}), that is, U_{1i}-U_{0i}> 0. The difference between the utility with and without ICTs adoption may be denoted as a latent variable ICT^*_{it} so that $ICT^*_{it} > 0$ indicates that the utility with ICT adoption exceeds the utility without adoption. While the utility difference cannot be directly observed, a household or an individual's propensity to adopt ICTs can be expressed in a linearized form as follows:

$$ICT^*_{ikt} = \beta_1 I_{it} + \beta_2 L_{it-1} + \beta_3 V_{it-1} + \varepsilon_{it} \tag{1}$$

$$ICT_{ikt} = 1\left[ICT^*_{ikt} \geq 0\right] \tag{2}$$

where ICT_{ikt} represents the i^{th} household or individual adopting the k^{th} ICT ($k = 1$ or 2 or 3, representing using computer or access to the internet or having a smartphone) in year t. I_{it} is a vector of the household head characteristics when $k = 1$ or 2, and the individual characteristics when $k = 3$; the characteristics of the household head or individual include age, education, and gender. $L_{it\text{-}1}$ is a vector of nonfarm jobs of the household head and household characteristics in 1-year lagged form; the household characteristics include the number of the other household members engaging in nonfarm jobs, farmland, and household size. $V_{it\text{-}1}$ is a vector of village characteristics in 1-year lagged form, including the percentages of households having a computer, access to the internet, and whether there is a telecom office in the village. 1[·] is an indicator function, denoting $ICT_{ikt} = 1$ if $ICT^*_{ikt} \geq 0$; otherwise, $ICT_{ikt} = 0$. β_1, β_2 *and* β_3 are the vector of parameters to be estimated. ε_{it} is a random error term, which is assumed to be normally distributed.

The logit model is used to estimate the above equations with and without the village fixed effect and also with and without year dummies. The village fixed effect estimation can control for all village level time-invariant factors that may affect the ICT adoptions, and year dummies can control yearly specific impacts. For correcting the potential estimation bias caused by the different sample sizes among different provinces and over time, the sample weights adjusted by the observations of each province in each year discussed in the data section are used in all regressions.

To investigate fruit producer's decision to use e-commerce to sell his/her fruit, we specify an adoption decision model as follow:

$$ECom_{it} = \gamma_1 I'_{it} + \gamma_2 L'_{it-1} + \gamma_3 V'_{it-1} + \epsilon_{it} \tag{3}$$

where $ECom_{it}$ is a dummy variable that equals 1 if the i^{th} household used e-commerce to sell its fruit in year t, and zero otherwise. I'_{it} is a vector of the characteristics of the decision-maker, including age, gender, and education. L'_{it-1} is a vector in 1-year lagged variables of having e-commerce training, a smartphone and a nonfarm job, and of the number of non-decision-maker household members with nonfarm jobs, farm land, being a member of a farmer's professional cooperative and the number of the relatives within three generations engaging in marketing. V'_{it-1} is a vector of village characteristics in 1-year lagged form, including having a post office or not, the distance from the village to the nearest agricultural market. ϵ_{it} is the random error term.

In order to assess the role of intergenerational support on fruit producer's decision to sell his/her fruit through e-commerce, we added the interaction variables between Child and the decision- maker's age and education in Equation (3). The models of adopting e-commerce are estimated for whole samples that include all four fruits studied and also by each fruit as well as with and without the village fixed or year effects.

5 | EMPIRICAL RESULTS

5.1 | Enabling and constraint factors affecting ICT adoption

Table 5 presents the estimation results based on a logit model. To check the robustness of the results, two alternative specifications are estimated: columns (1), (3) and (5) consider the year effect (a dummy for each year), and columns (2), (4), and (6) consider both the year effect and the village fixed effect. Generally, the results are consistent, hence we focus on the latter set of estimation results.

Columns (2) and (4) report the estimation results of households having a computer and access to the internet. The results provide statistically significant (at the 1% level) evidence of the digital divide in terms of age and education (rows 1 and 2). A year increase in the age of the household head is associated with a lower probability of households using computers (by .9%) (column 2) and having internet access (.7%, column 4). Furthermore, a household head with 1 year more schooling has a 1.4% higher probability of using a computer and a .9% higher probability of getting access to the internet. These results are consistent with the

TABLE 5 Estimation results of households having computers and access to internet and individuals having smartphone

	Computer		Internet		Smartphone	
	(1)	(2)	(3)	(4)	(5)	(6)
Household head characteristics						
Age $_{it}$	−.007***	−.009***	−.007***	−.007***	−.011***	−.012***
	(.001)	(.001)	(.001)	(.001)	(.000)	(.000)
Education $_{it}$	.012***	.014***	.008***	.009***	.014***	.015***
	(.003)	(.003)	(.002)	(.002)	(.001)	(.001)
Gender $_{it}$	−.104	−.118*	−.012	−.014	.055***	.056***
	(.063)	(.070)	(.055)	(.058)	(.004)	(.004)
Nonfarm $_{it-1}$	−.037	−.048*	.019	.016	.089***	.080***
	(.026)	(.028)	(.024)	(.024)	(.006)	(.006)
Household characteristics						
Others_nonfarm $_{it-1}$	.042***	.042***	.051***	.064***	.007***	.015***
	(.008)	(.009)	(.008)	(.009)	(.002)	(.002)
Farmland $_{it-1}$	.033***	.035***	.017**	.035***	.009***	.010***
	(.010)	(.011)	(.008)	(.011)	(.003)	(.003)
Household size $_{it-1}$	.005	.017***	.022***	.018***	−.006***	−.008***
	(.004)	(.005)	(.004)	(.005)	(.001)	(.001)
Village characteristics						
Neighbor computer $_{it-1}$	.008***	.004***	−.000	.002*	.000	.001
	(.000)	(.001)	(.000)	(.001)	(.000)	(.000)
Neighbor internet (smartphone) $_{it-1}$	−.000	.001**	.006***	.004***	.005***	.005***
	(.000)	(.000)	(.000)	(.000)	(.000)	(.001)
Telecom $_{it-1}$	−.006	−.003	.015	.038	.013***	.008
	(.020)	(.014)	(.019)	(.029)	(.005)	(.019)
Village fixed effect	No	Yes	No	Yes	No	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13,570	13,570	13,570	13,570	45,933	45,933

Note: The estimated parameters are marginal effects. Neighbor internet is introduced into the specifications (1)-(4), while neighboring smartphone is introduced into the specifications (5)-(6). Robust standard errors clustered at the household level or individual level are in parentheses. *, **, and *** indicate $p < .10$, $p < .05$, $p < .01$, respectively.

previous findings that younger and higher educated farmers are more likely to adopt ICTs (e.g., Aker & Mbiti, 2010; Leng et al., 2020).

Columns (2) and (4) also show that nonfarm employment, farm size and household size are significantly associated with the use of a computer and internet by rural households. Nonfarm employment positively correlates with using a computer and internet (row 5), which can be attributed to the benefits stemming from nonfarm employment such as improvement of human capital, enhancement of income and also extension of social networks (Ma et al., 2018). However, nonfarm employment of the household head does not relate to the household's access to the internet (row 4). This may reveal that rural households' use of the internet is mainly driven by their children. Additionally, those households with more cultivated land are more likely to have computers and internet access. This may be due to the fact that farmers operating more land have a stronger initiative to improve the efficiency of agricultural production through good use of ICTs (Aker, 2011), or they can better afford to buy computers and get access to the internet (Ma, 2018).

The estimated parameters in columns (2) and (4) show that the intensity of using a computer (or internet) by the other households in the village is significantly and positively associated with the household's using a computer (or internet) (rows 8 and 9). These results provide strong evidence for the existence of neighborhood effects or exogenous social effects (Manski, 1993) and social learning relating to the adoption of ICTs among rural households.

Column (6) reports the estimation results of individuals' having a smartphone. Here nonfarm employment of other family members and farmland of the household, and the percentage of farmers having a smartphone within the whole village are all significantly associated with individuals' use of a smartphone. Men are also more likely (by 5.6%, row 3) to use a smartphone, as are those employed in nonfarm sectors (by 8%, row 4).

5.2 | Enabling and constraining factors affecting the use of e-commerce to sell fruit

Equation (3) was estimated with the following three sets of alternative regressions:

1. Using the whole sample for all 4 products and by each product without considering the village fixed effect, which can reveal the effects of observed village infrastructure that may not vary much over time (Table A3);
2. Using the whole sample for all 4 products and by each product using the village fixed effect estimation, which can better control for all unobserved village level characteristics that do not change over time (Table 6);
3. Considering the role of children using the village fixed effect (Table 7).

Given the small sample size and limited variation within households, the estimation results not using clustered robust standard errors are reported for analysis in the text (Tables 6 and 7), while the results using clustered robust standard errors are reported in the Appendix (Tables A3 and A4).

The estimation results presented in Table A3 and Table 6 are consistent for nearly all variables except for two village characteristics. Without using the village fixed effect estimation, the presence of a post office in the village positively correlates with households' selling fruit through e-commerce, while the distance to the nearest agricultural market negatively associates with using e-commerce. The convenience of logistics, as a prerequisite for e-commerce infiltration, directly affects the transaction cost of farmers' online sales. Farmers' willingness to engage in e-commerce would be hindered by the lack of postal services or the difficulties to efficiently obtain agricultural market information in the nearby area (Couture et al., 2021). As we would expect, when the models are estimated with the village fixed effect, these impacts disappear because the variations of these two variables are mainly among villages rather than over time. The following discussions focus on the results presented in Table 6 with the village fixed effect estimation.

The estimation results also show a strong e-commerce divide among farmers. For example, the estimated parameter for age of decision-maker is significant and negative for the whole sample (column 1, Table 6) and for three of four products (apples, peaches and walnuts, columns 2–4). For 1-year increase in age, a .6% decline for whole sample and about .7% to 1.0% for apples, walnuts and peaches can be observed in the probability of fruit producers selling their fruits online (row 1). The years of schooling are also significantly and positively associated with farmers' participation in e-commerce for whole sample, and for walnuts and kiwifruit (row 2). For 1 year increase of schooling, the average probability of fruit producers engaging in e-commerce increases by 1.6% (row 2). When the models are estimated by each fruit, only walnuts and kiwifruit are significant, which may be due to the fact that the size of sample by product is not large enough. Younger and more educated farmers are more likely to sell their products through e-commerce, which is also in line with previous studies (Luo & Niu, 2019). Interestingly, similar to the finding on access to the internet, we find that the use of e-commerce is not biased in gender (row 3).

A decision-maker who attended any e-commerce training and had a smartphone is significantly and positively associated with his/her using online sales (rows 4 and 5, Table 6). Undoubtedly, the specialized e-commerce training provided by the local government is beneficial for farmers to grasp the skills required for successfully operating e-commerce, which also reduces the cost of learning and inspires farmers' willingness to adopt e-commerce (Peng et al., 2021). Additionally, as an indispensable hardware device for engaging in e-commerce by small farms, the use of smartphones by the decision-makers improves the convenience of online sales.

The positive relationship between decision-makers' nonfarm employment and using e-commerce is evidenced in the full sample, and statistically significant in peaches but not in the other three fruits (row 6, Table 6). The generally positive impact is consistent with previous studies (e.g., Liu et al., 2021). Insignificant estimated parameters based on the regression by product may be due to factors other than the small sample size. On the one hand, nonfarm employment broadens farmers' horizons and expands their social networks, enhancing their acceptance of new technologies. On the other hand, e-commerce is labor intensive and could clash with nonfarm work obligations (Li et al., 2021). Moreover, peaches are more perishable than apples and walnuts, therefore the market window is shorter, which tends to have a smaller impact on the decision-makers' nonfarm work.

The results also demonstrate that farms with better resource endowments and farmers with wider social networks are more inclined to engage in e-commerce (rows 7–10). Specifically, fruit producers with more family members employed in the nonfarm sector and larger farm size

AGRICULTURAL ECONOMICS The Journal of the International Association of Agricultural Economists IAAE WILEY

TABLE 6 Estimation results of fruit producers using e-commerce: With village fixed effect and year dummies

	Full sample (1)	Apple (2)	Peach (3)	Walnut (4)	Kiwifruit (5)
Decision-maker characteristics					
Age $_{it}$	−.006***	−.007*	−.010***	−.008***	−.004
	(.002)	(.004)	(.004)	(.002)	(.003)
Education $_{it}$	.016***	−.015	.009	.017**	.022***
	(.004)	(.012)	(.010)	(.008)	(.007)
Gender $_{it}$	−.003	−.113	.059	.027	.033
	(.032)	(.079)	(.068)	(.057)	(.069)
Train $_{it-1}$	.151***	.166***	.174***	.240***	−.020
	(.026)	(.052)	(.057)	(.049)	(.059)
Smartphone $_{it-1}$	.130***	.204***	.159**	.042	.093*
	(.032)	(.061)	(.081)	(.071)	(.055)
Nonfarm $_{it-1}$	.057**	−.021	.157***	.009	.079
	(.027)	(.058)	(.046)	(.061)	(.053)
Household characteristics					
Others_nonfarm $_{it-1}$	.081***	.165***	.081**	.023	.062***
	(.014)	(.032)	(.037)	(.027)	(.022)
Farmland $_{it-1}$	.069***	.009	.146**	−.027	.066***
	(.022)	(.036)	(.061)	(.040)	(.025)
Cooperation $_{it-1}$	.055*	.126**	.140*	−.077	.006
	(.031)	(.060)	(.073)	(.072)	(.052)
Relative $_{it-1}$	.007*	.008	.004	.013***	.001
	(.004)	(.008)	(.027)	(.004)	(.006)
Village characteristics					
Express $_{it-1}$	−.058	.109	−.090	−.137	−.047
	(.059)	(.104)	(.123)	(.125)	(.146)
Distance $_{it-1}$	−.004	.027	.027	−.008	−.004
	(.005)	(.022)	(.045)	(.025)	(.006)
Observations	1,090	243	235	362	250

Note: The estimated parameters are marginal effects and the robust standard errors are in parentheses. *, **, and *** indicate $p < .10$, $p < .05$, $p < .01$, respectively.

show a stronger tendency to selling their fruit online (rows 7 and 8). Moreover, being a member of a farmers' professional cooperative and the number of relatives within three generations operating marketing business, which directly measure the household's social network connection, are both positively associated with fruit producers' engagement in e-commerce (rows 9 and 10). The potential channels for the above relationships include experience exchanges, imitative learning, and sales cooperation, etc. (Cristobal-Fransi et al., 2020).

The results presented in Table 7 further consider the likely impact of intergenerational support on fruit producer's engagement in e-commerce. As discussed early, we measure the intergenerational support by whether the farmer has any child having a job with a high level of social network connection who can contact many people through using his/her ICT devices. Although the impact of intergenerational support on the adoption of new technologies has been discussed in the existing literature (Liikanen et al., 2004; Freeman et al., 2020), little is known about the potential role of sale decision-maker's children in his/her involvement in online sales.

As shown in column (1) of Table 7, the estimation parameter of *Child* is positively significant at a 5% level for whole sample. The unexpected negative sign of *Child* in the specification for apples may be caused by multicollinearity under small sample (the correlation coefficient between *Child* and *Age * Child* is .8 and the estimated parameter of *Child* is positive and significant at 5% level when *Age * Child* is eliminated). The interaction items (*Age * Child*, *Education * Child*) are positively and negatively significant at a 10% and 5% level respectively for the whole sample (rows 3 and 5). For the fruit producer without any child's help (farm A), the probability of using e-commerce

TABLE 7 Estimation results of fruit producers using e-commerce with the village fixed and year dummies: Considering the role of decision-maker's children

	Full sample (1)	Apple (2)	Peach (3)	Walnut (4)	Kiwifruit (5)
Decision-maker characteristics					
Child $_{it}$	.107**	−.275*	−.182	.272***	.117
	(.047)	(.160)	(.137)	(.059)	(.073)
Age $_{it}$	−.008***	−.010**	−.010***	−.014***	−.004
	(.002)	(.004)	(.004)	(.003)	(.003)
Age $_{it}$ * *Child* $_{it}$	.008*	.065***	.022	.001	.003
	(.004)	(.017)	(.017)	(.006)	(.006)
Education $_{it}$	.018***	−.015	.006	.009	.033***
	(.005)	(.012)	(.011)	(.009)	(.009)
Education $_{it}$ * *Child* $_{it}$	−.023**	−.004	−.010	−.008	−.057***
	(.009)	(.037)	(.030)	(.014)	(.016)
Gender $_{it}$	−.012	−.100	.063	−.009	.014
	(.032)	(.073)	(.063)	(.053)	(.061)
Train $_{it\text{-}1}$	.138***	.162***	.178***	.216***	−.060
	(.026)	(.045)	(.057)	(.050)	(.050)
Smartphone $_{it\text{-}1}$	.151***	.329***	.156*	.016	.152***
	(.032)	(.082)	(.088)	(.059)	(.055)
Nonfarm $_{it\text{-}1}$	.072***	−.004	.159***	.027	.074
	(.028)	(.058)	(.046)	(.057)	(.053)
Household characteristics					
Others_nonfarm $_{it\text{-}1}$	.043***	.148***	.093**	−.033	−.006
	(.015)	(.032)	(.039)	(.026)	(.027)
Farmland $_{it\text{-}1}$	.070***	.032	.152***	−.047	.066**
	(.022)	(.044)	(.057)	(.035)	(.026)
Cooperation $_{it\text{-}1}$	.060*	.119*	.118	−.020	−.043
	(.031)	(.061)	(.072)	(.069)	(.055)
Relative $_{it\text{-}1}$	.007**	.011	.004	.011***	−.003
	(.004)	(.008)	(.026)	(.004)	(.005)
Village characteristics					
Express $_{it\text{-}1}$	−.071	.096	−.068	−.092	−.044
	(.060)	(.097)	(.116)	(.105)	(.143)
Distance $_{it\text{-}1}$	−.004	.014	.020	−.005	−.005
	(.004)	(.020)	(.042)	(.024)	(.006)
Observations	1,090	243	235	362	250

Note: The estimated parameters are marginal effects and the robust standard errors are in parentheses. *, **, and *** indicate $p < .10$, $p < .05$, $p < .01$, respectively.

decreases by .8% for a 1-year increase in age (row 2), but for the fruit producers with their children's help (farm B), the corresponding impact closes to 0 (-.8% + .8%) (rows 2 and 3). Similarly, farm A's probability of using e-commerce decreases by 1.8% for 1 year less schooling (row 4), but for farm B, this impact is more than offset by the help from children (-1.8% + 2.3% = .5%). These results suggest that the constraints for older and less educated fruit producers to engage in e-commerce can be significantly eased with the help of their children through making good use of children's advantages in broad access to market information, and extension of social network for products online sales.

Columns (2) to (5) of Table 7 present the results by apple, peach, walnut, and kiwifruit. Specifically, the positive role of capable children on relieving the constraints of their parents engaging in e-commerce is particularly evidenced in apples and kiwifruit (row 3 and row 5).

6 | CONCLUDING REMARKS

Using two sets of household survey datasets in 2015–2019, we document the trends in ICT application and e-commerce adoption to sell fruit in the past 5 years in rural China, empirically test the enabling and constraining factors facing farmers' using ICTs and e-commerce, and further discuss the inequality issues of digital technology application in rural China.

The results show that, even though the increase in ICT adoption has been impressive, there is still plenty of room for further penetration (particularly computers) in rural China. While e-commerce is emerging and clustering in some economically developed regions, the average adoption of e-commerce for rural households in China is still limited.

The econometrical results suggest that human capital (e.g., age, education, skills or capacity), social networks (relatives and cooperation), resource endowment (farm size and nonfarm employment), ICT infrastructure, and location are the main determinants explaining household's or individual's adoption of ICTs, and the producer's selling their fruits through e-commerce. In addition to the dispersion in ICT adoption among regions and farmers, a new digital divide on e-commerce adoption has also emerged in rural China. The aged and less educated farmers and the farmers with less training, weak social networks, and limited resource endowments encounter more constraints in engaging in e-commerce than their counterparts.

This study also provides strong evidence of intergenerational support for farmers from their children to engage in e-commerce to sell their farm products. This is an effective pathway to relieve the constraints of the aged and less educated farmers to participate in e-commerce. However, there are also many aged and less educated farmers without this kind of support from their children. They have fallen much behind in using e-commerce, and this divide will increase as they grow older.

The results have several policy implications. First, while the spread of ICTs and e-commerce has been rapid and is expected to reshape agriculture and rural development in the future, a more inclusive development strategy should be pursued now. Digital technology can be driven by market forces and further accelerate the diffusion of ICTs and e-commerce in rural areas in the future, but without the policies and investment to support those who are left behind in digital technology application, new inequalities will occur in rural areas in the digital era. Second, more support should be provided to disadvantaged rural households and farmers through skills training, social network improvement, farm size expansion, farmers' cooperative development and other capacity building programs. Particular attention should be given to the older and less educated farmers and farmers in the less developed regions. Last but not least, investment in ICT infrastructure and enhancing storage facilities and logistics for e-commerce, particularly in less developed rural areas, are essential to advance equality in the course of ICT diffusion and e-commerce development.

ACKNOWLEDGMENTS

This work is supported by the National Natural Science Foundation of China (No.71934003), the National Social Science Foundation of China (19ZDA002) and Alibaba Group (No. JLA50WBJ1210043).

REFERENCES

Aker, J. C. (2011). Dial "A" for agriculture: A review of information and communication technologies for agricultural extension in developing countries. *Agricultural Economics*, *42*, 631–647. https://doi.org/10.1111/j.1574-0862.2011.00545.x

Aker, J. C., & Mbiti, I. M. (2010). Mobile phones and economic development in Africa. *The Journal of Economic Perspectives*, *24*(3), 207–232. https://doi.org/10.1257/jep.24.3.207

Ali Research. (2020). 1% change, 2020 China Taobao Village research report. http://www.aliresearch.com/ch/information/informationdetails?articleCode=126860487966199808&type

China Internet Network Information Center (CNNIC). (2021). The 47th China statistical report on internet development. http://www.cac.gov.cn/2021-02/03/c_1613923423079314.htm

Couture, V., Faber, B., Gu, Y., & Liu, L. (2021). Connecting the countryside via e-commerce: evidence from China. *American Economic Review: Insights*, *3*(1), 35–50. https://doi.org/10.1257/aeri.20190382

Cristobal-Fransi, E., Montegut-Salla, Y., Ferrer-Rosell, B., & Daries, N. (2020). Rural cooperatives in the digital age: an analysis of the Internet presence and degree of maturity of agri-food cooperatives' e-commerce. *Journal of Rural Studies*, *74*, 55–66. https://doi.org/10.1016/j.jrurstud.2019.11.011

Deichmann, U., Aparajita, G., & Deepak, M. (2016). Will digital technologies transform agriculture in developing countries. World Bank Policy Research Working Paper. No., *7669*. World Bank.https://openknowledge.worldbank.org/handle/10986/24507?locale-attribute=fr

Enoch, M. K., Elisabeth, F., & Matin, Q. (2014). Mobile money, smallholder farmers, and household welfare in Kenya. *Plos One*, *9*(10), e109804. https://doi.org/10.1371/journal.pone.0109804

Freeman, S., Marston, H. R., Olynick, J., Musselwhite, C., Kulczycki, C., Genoe, R., & Xiong, B. (2020). Intergenerational effects on the impacts of technology use in later life: insights from an international, multi-site study. *International Journal of Environmental Research and Public Health*, *17*(16), 5711. https://doi.org/10.3390/ijerph17165711

Guo, Y., & Chen, P. (2011). Digital divide and social cleavage: case studies of ICT usage among peasants in contemporary China. *The China Quarterly*, *207*, 580–599. https://doi.org/10.1017/S030574101100066X

Hartje, R., & Hübler, M. (2017). Smartphones support smart labour. *Applied Economics Letters*, *24*, 467–471. https://doi.org/10.1080/13504851.2016.1203054

ITU. (2018). Measuring the information society: International Telecommunication Union Annual Report. Available at https://www.itu.int/en/ITU-D/Statistics/Documents/publications/misr2018/MISR-2018-Vol-1-E.pdf

Leng, C., Ma, W., Tang, J., & Zhu, Z. (2020). ICT adoption and income diversification among rural households in China. *Applied Economics*, *52*(33), 3614–3628. https://doi.org/10.1080/00036846.2020.1715338

Li, X. K., Guo, H. D., Jin, S. Q., Ma, W. L., & Zeng, Y. W. (2021). Do farmers gain internet dividends from e-commerce adoption? Evidence from China. *Food Policy*, *101*(3), 102024. https://doi.org/10.1016/j.foodpol.2021.102024

Liikanen, J., Stoneman, P., & Toivanen, O. (2004). Intergenerational effects in the diffusion of new technology: The case of mobile phones. *International Journal of Industrial Organization*, *22*(8-9), 1137–1154. https://doi.org/10.1016/j.ijindorg.2004.05.006

Liu, M., Zhang, Q., Gao, S., & Huang, J. K. (2020). The spatial aggregation of rural e-commerce in China: An empirical investigation into Taobao villages. *Journal of Rural Studies*, *80*, 403–417. https://doi.org/10.1016/j.jrurstud.2020.10.016

Liu, M., Min, S., Ma, W. L., & Liu, T. J. (2021). The adoption and impact of e-commerce in rural China: Application of an endogenous switching regression model. *Journal of Rural Studies*, *83*, 106–116. https://doi.org/10.1016/j.jrurstud.2021.02.021

Luo, X., & Niu, C. (2019). E-commerce participation and household income growth in Taobao villages, World Bank Policy Research Working Papers. https://doi.org/10.1596/1813-9450-8811

Ma, W., Grafton, R. Q., & Renwick, A. (2018). Smartphone use and income growth in rural China: Empirical results and policy implications. *Electronic Commerce Research*, *20*(4), 713–736. https://doi.org/10.1007/s10660-018-9323-x

Manski, C. F. (1993). Identification of endogenous social effects: The reflection problem. *The Review of Economic Studies*, *60*(3), 531–542. https://doi.org/10.2307/2298123

Nakasone, E., Torero, M., & Minten, B. (2014). The power of information: The ICT revolution in agricultural development. *Annual Review of Resource Economics*, *6*, 533–550. https://doi.org/10.1146/annurev-resource-100913-012714

National Bureau of Statistics of China (NBSC). (2020). *China Rural Statistical Yearbook 2020*. China Statistics Press.

Peng, C., Ma, B., & Zhang, C. (2021). Poverty alleviation through e-commerce: Village involvement and demonstration policies in rural China. *Journal of Integrative Agriculture*, *20*(4), 998–1011. https://doi.org/10.1016/S2095-3119(20)63422-0

The Ministry of Agriculture and Rural Affairs of China. (2020). Expert Advisory Committee on Agricultural and Rural Informatization, Digital Village Development Report of China in 2020, http://www.cqxumu.com/upload/2020/11/637423294227055808.pdf

The Ministry of Commerce of China. (2021). Person in charge of E-commerce Department of the Ministry of Commerce talks about the development of online retail market in 2020 in China. http://www.mofcom.gov.cn/article/resume/n/202102/20210203036186.shtml

Zeng, Y. W., Guo, H. D., & Jin, S. Q. (2018). Does e-commerce increase farmers' income? Evidence from Shuyang County, Jiangsu Province, China. *Chinese Rural Economy*, *2*, 49–64. (in Chinese).

How to cite this article: Huang, J., Su, L., Huang, Q., & Liu, X. (2022). Facilitating Inclusive ICT application and e-Commerce development in rural China. *Agricultural Economics*, *53,* 938–952. https://doi.org/10.1111/agec.12728