Facilitating Inclusive ICT Application and e-Commerce Development in Rural China

by Jikun Huang, Lanlan Su, Qiwang Huang, and Xinyu Liu

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Abstract

Application of information and communication technologies (ICTs) in general and e-commerce development in particular is 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' adoption and e-commerce in rural China and farmers' selling fruits online in more developed e-commerce villages in two provinces, and examines the enabling and constraint factors for farmers to 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 network, resource endowment, ICT infrastructure and locations are the main determinants of household's or individual's adoption of ICTs, and the producer selling their fruits through e-commerce. Moreover, this study provides new and strong evidence of intergenerational support for aged and less schooling farmers from their children to engage in online sale. However, this study also points out that a new digital divide on the spreads of ICTs and e-commerce has emerged across regions and among farmers in rural China. The paper concludes with several policy implications on fostering rapid and inclusive ICT application and e-commerce development in rural areas in the coming digital era.

Keywords: ICTs; e-commerce; inclusiveness; digital divide; rural China

1. Introduction

Information and communication technologies (ICTs) has 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 the 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%) and 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 having computer, and 73% for owing a mobile phone) in the developing countries (ITU, 2018). In the developing countries, there is also lag gap in ICT's spread between rural and urban (Nakasone et al., 2014; Deichmann et al., 2016).

Similar to the global trends of ICT adoptions, China has also experienced a rapid expansion of ICTs application and has made great efforts to reduce the gap between rural and urban since the early 2000s. Nationally, the penetration rate of internet increased from 16% in 2007 to 70% in 2020; the number of internet user increased from 210 million to 989 million, and mobile phone subscriptions rose from 50 million 986 million over the same period (China Internet Network Information Center or CNNIC, 2021). In 2007, the rural internet penetration rate was only 7%, this was much lower than the 26% penetration rate in urban. However, the growth rate in rural has been much higher due to the increasing efforts by government and private sector. By 2020, while the internet penetration rate (80%) in urban was about 3 times of that in 2007, it was 8 times in rural (56%) over the same period. Facilitating rural ICT development was first time included in the Five-Year Plan of the National Economic and Social Development (the Tenth Five-Year Plan) that was released in 2001. Hereafter, the No. 1 Central Document, the most important annual policy document in China, in 2005 specifically announced a plan for improving agricultural informatization, and since then the central and local governments have constantly emphasized the importance of ICT applications in rural China. Major efforts include the increasing investment in rural ICT infrastructure, broadband village construction, capacity building and training, and policy supports for rural e-commerce (the Ministry of Agriculture and Rural Affairs, 2020).

Driven by the significant increase in the internet penetration, e-commerce has also developed rapidly in China in recent years. For example, the total value of online sales increased from 130 billion yuan in 2008 to 11,760 billion yuan in 2020, its share in the total retail values increased from 1% to 30% over the same period (the Ministry of Commerce, 2020). While the online sales mainly occur in urban, it has also emerged in rural. The value of online sales in rural rose from 353 billion yuan in 2015 to 1,800 billion yuan in 2020, accounting for about 15% of the national online retail value in 2020 (the Ministry of Commerce, 2021). In terms of agricultural products, online retail value reached 398 billion yuan in 2019. Moreover, Taobao Village with large scale of e-commerce business in rural has been emerging. It started in 2009, and the number of Taobao Villages reached 5,425 in 2020. About 13% of Taobao Villages had annual transactions exceeding 100 million yuan in 2019 (AliResearch, 2020). Although the share of Taobao Villages was less than 1% of total villages (690,000 villages) in 2020, given its rapid growth in recent years, it is expected that this share will increase significantly in the future.

In the literature on adoptions of ICTs and e-commerce by rural households, there has been increasing number of empirical studies based on household surveys in many countries. These studies showed that human capital, household resources (e.g., access to land and credit, etc.) and local ICT infrastructure are major factors affecting farmers' adoptions of ICTs (e.g., Aker & Mbiti, 2010; Chavula, 2014; Enoch et al., 2014; Ma et al., 2018) and e-commerce (e.g., Kabango & Asa, 2015; Ouyang et al., 2017; Ma et al., 2020; Li et al., 2021; Liu et al., 2021). However, there are also concerns on 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., Luo & Niu, 2019; Liu et al., 2020) across regions and among population.

Overall goal of this study is to further examine the major factors affecting rural household's adoptions 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's adoption that come from the primary household surveys with the national representative samples in rural China in 2015-2019. Second, in addition to provide new evidences of major factors affecting farmers' selling their agricultural products through e-commerce discussed above, we find that a pathway of older and less educated farmers to break their barriers in using e-commerce through their children who work non-farm and have better network. Last but not the least, we pay particular attention to the inequity of ICT and e-commerce adoptions between regions and among rural households within the same village. The results of this study should have important policy implications for fostering inclusive adoptions of ICTs and e-commerce in not only China but also other developing countries.

The rest of this paper 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 adoptions 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

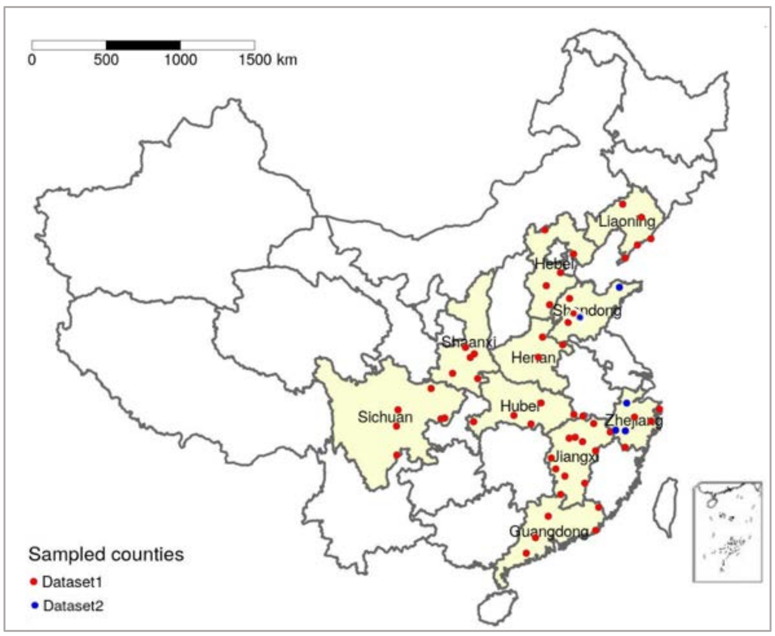
Two sets of household survey data used in this study are from the national representative surveys (Dataset 1) and e-commerce survey (Dataset 2), both were conducted by authors. Dataset 1 is used to present the overall trends of using ICTs and e-commerce by rural households in 10 provinces surveyed from 2015 to 2019 and examine enable or constraint factors affecting farmers' uses of ICTs over the same period. Because the rural household selling their products online was still only about 2% in 2019 based on Dataset 1 (see more discussion later), we conducted the other e-commerce survey in more advanced e-commerce counties in Zhejiang and Shandong provinces (Dataset 2) and used this Dataset to examine enable or constraint factors affecting farmers' uses of e-commence to sell their products 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 locations of each surveyed county in each of 10 provinces are 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 5 counties in each of other 7 provinces). The same procedure was also applied to select 2 townships from each county except the counties from Jiangxi (3 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 2,480 households (1,400 =20x1x2x5x7 in the 7 provinces and 1,080=10x3x3x12 in Jiangxi province) were selected for survey. The first wave of survey was conducted in the early 2017 with data in 2015 and 2016; the second wave of survey for the same households was conducted in the end of 2019 with data in 2017-2019. At end, a total of 2,526 households (1,451 in the 7 provinces and 1,075 in Jiangxi province) were actual surveyed samples used in this study. The reason for the slightly higher number of actual survey sample than the designed sample is due to replacement of some new households in 2019 for the households surveyed in 2017 but not be able to follow up their survey in 2019.



Map 1. National representative surveys in 10 provinces and e-commerce survey in 2 provinces

Note: The red dot represents the county location of household survey for Dataset 1, and blue dot represents the county location of e-commerce survey for Dataset 2.

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 all counties were divided evenly into three groups. One county was randomly selected from each group. In each county, two townships were selected using the same procedures, which was also applied to select two villages from each township. Within each sampled villages, 10 households were randomly selected. A total of 240 household (10x2x2x3x2) were surveyed in 2017 for data in 2015 and 2016, 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, the village leaders were interviewed to collect information on the infrastructure of ICTs in the village in the past few years.

Because the surveyed samples differ among provinces, particularly between Jiangxi and the other 7 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. Specifically, for the statistics and regression analysis at the household level, the sample weights are calculated based on the number of households surveyed in each year in each province; for the statistics and regression analysis at the individual level, the sample weights are calculated based on the number of individuals surveyed in each year in each province. Consequently, the household or individual from the same province has the same weight, but the household and individual from each province in each year have different weights.

2.1.2 The adoptions of major ICTs by rural households and individuals

Although there are many ICT's applications by rural households, based on our survey, access to internet and having computer in a household as well as owning smartphone by individual are the major applications of ICTs. Individual with or without ICT's application in this paper is defined as household member with at least 16 years old. Figure 1 shows the adoptions of three major ICTs in rural China from 2015 to 2019 based on Dataset 1. Among the three indicators, the percentage of households with internet access increased faster than the percentages of households with computer and individuals with smartphone. By 2019, the percentage of households with computer and access to internet reached 30% and 83%, respectively; and the percentage of individuals with smartphone reached 71%. Our survey results on the internet and smartphone uses are consistent with the statistics (measured for whole population) reported by CNNIC (2021) if the internet and smartphone penetrations in our data are also measured based on household population rather than household or individual with at least 16 years old.

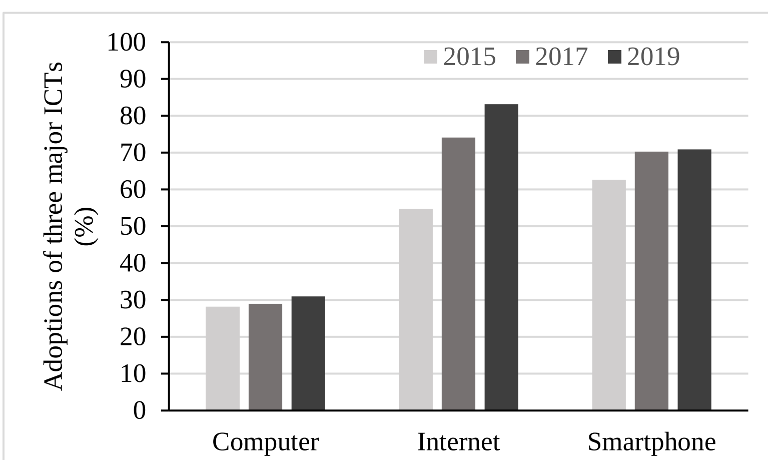
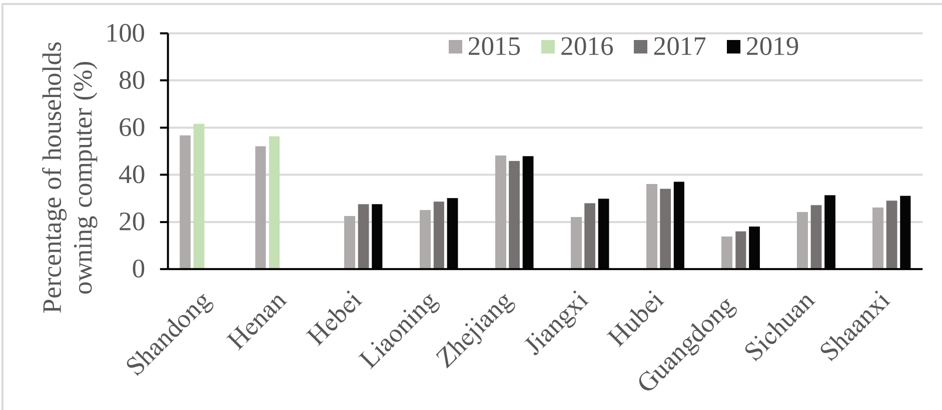


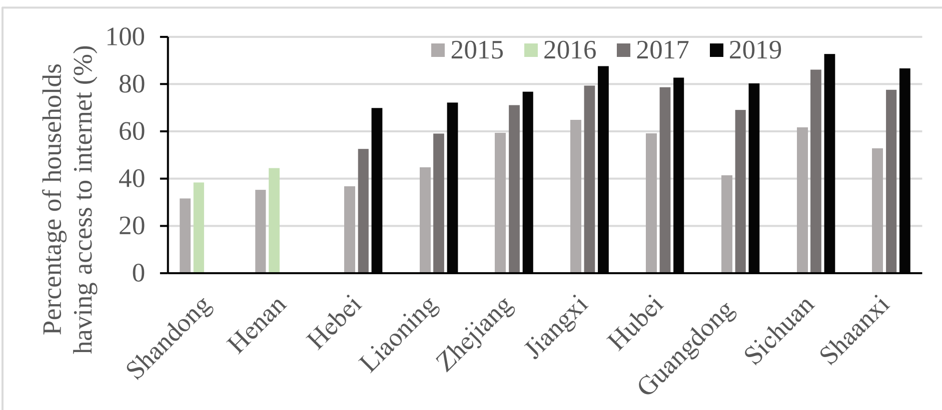
Figure 1. Adoptions of three major ICTs by rural households or individuals in 2015-2019

Source: Authors' own surveys.

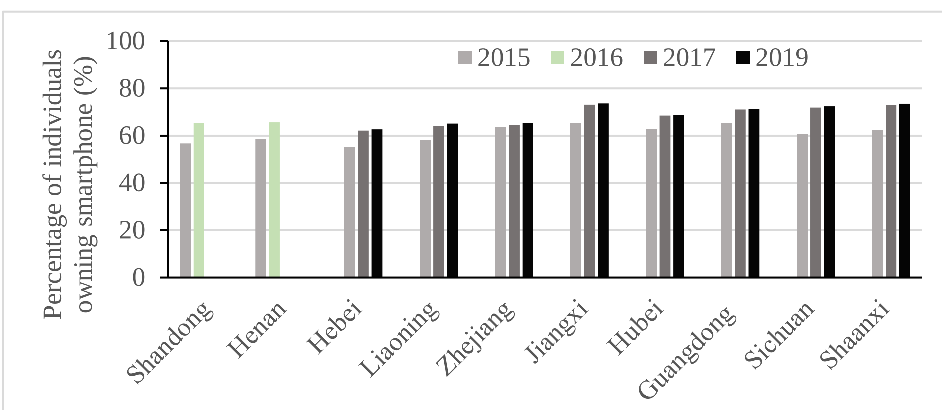
Figure 2 shows the adoptions of three major ICTs by province in 2015-2019. While the adoption rates for all three indicators had increased in nearly all provinces over time, level of adoption differs largely among provinces for computer and internet. But, the percentage of individuals using smartphones did not vary significantly among provinces.



Computer



Internet access



Smartphone

Figure 2. The adoptions of three major ICTs by province in rural China, 2015-2019

Source: Authors' surveys.

In terms of the households having computer, although computer use in rural areas in all surveyed provinces have increased, it is not very common in many provinces. For example, even by 2019, less than one third of rural households had a computer in Hebei, Liaoning, Jiangxi, Guangdong, Sichuan and Shanxi, indicating that there is still a large room for spread of computers in rural China. A slight decline in the households having computer in Zhejiang and Hubei provinces in 2017 is due to the adjustment of the samples of these two provinces in the second-round of surveys.

On the internet access, the statistics show that its penetration rate in all surveyed provinces were close to or more than 70% in 2019. The growth rates in Hebei, Guangdong and Liaoning provinces were relatively higher than those of other sampled provinces in 2015-2019. It is worth noting that some underdeveloped western provinces such as Sichuan and Shaanxi provinces have also experienced an obvious growth in internet access in the past five years. This is largely due to the increasing policy support from the central and local governments to facilitating the diffusion of ICTs in underdeveloped areas in recent years.

Despite its rapid development, our survey data show that e-commerce is still not a common marketing channel for farmers to sell their products. In 2015, less than 1% of farmers had sold their products online. By 2019, although the number was more than double, there were still only about 2% of them sold their products through e-commerce. When we asked farmers what is the most important reason for not using e-commence, about two third responded the lack of operating e-commerce skills, about 30% of them said the lack of fresh-keeping and storing facilities, and the rest included the lack of packing and marketing skills and the high logistics cost.

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 selling their products online by 2019 in our national 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 the bulk commodities such as grain and edible crops that often need processing. With the selected fruits, then we selected the counties that produce these fruits with more advanced in e-commerce. They are Qixia county for apple and Feicheng county for peach in Shandong province, Linan county in Zhejiang province for walnut, 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 apple, peach and kiwifruit. For walnut, the samples were expanded to 6 villages. In each of sampled villages, we aimed to randomly select 10 to 15 households based on the size of villages. Finally, we selected 225 households for the first round survey (for data in 2015-2017) conducted in the early 2018. In the second round of survey in the early 2020, we were able to follow up only 198 households but added 45 new households to have a total sample of 243 households.

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 fruits in our studied villages. Specifically, the proportions of farmers using e-commerce to sell apple, peach, walnut and kiwifruit were 25%, 17%, 35%, and 47%, respectively, in 2015; these proportions increased to 45%, 60%, 48%, and 83%, respectively, in 2019. Meanwhile, the increase in using the e-commerce differed among products. This could be attributed to the differences in the product characteristics, the requirements for timely selling the product, and convenience of local logistics conditions.

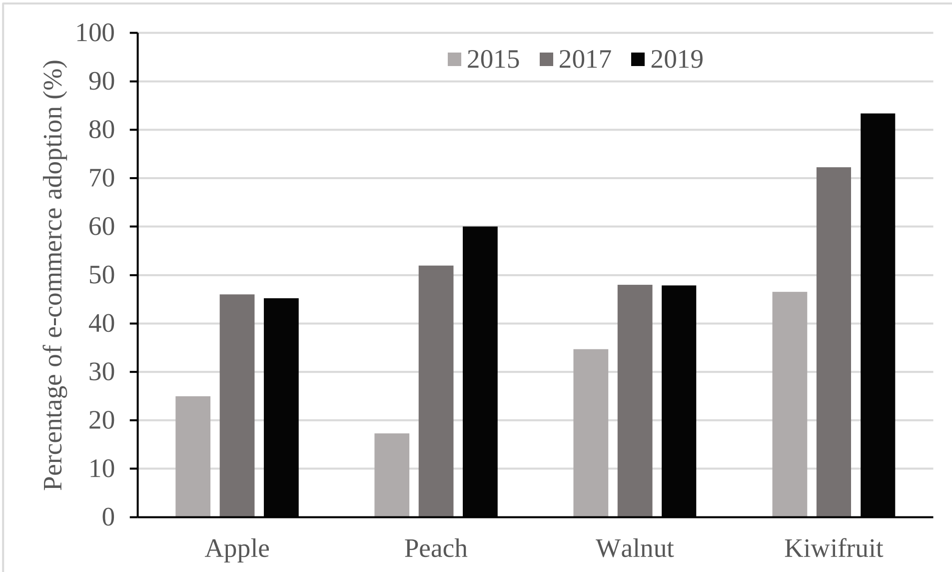


Figure 3. The percentage of households selling their fruits online in the selected villages in Shandong and Zhejiang in 2015-2019

Source: Authors' surveys.

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 variable 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 the national statistics in rural China. These include average household head age, gender, education, farm land and household size (National Bureau of Statistics of China or NBSC, 2020a). On the percentage of rural labors had non-farm job, it was 41.5% in 2019 in the official statistics (NBSC, 2020b). We reported the percentage of individual (with at least 16 years old) had non-farm job was 42% in 2019 (Table 3).

On ICTs infrastructure, our surveyed villages seem have better infrastructure. Nearly 20% of the sampled villages had at least one business office established by the China Mobile or China Unicom, the two major providers of mobile communication services in rural China. More importantly, the surveyed villages have achieved universal coverage of mobile phone services and broad-band internet since 2016.

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 (or adult) has a smartphone, 0 otherwise
Household head or individual characteristics	
Age	Age of household head or individual (year)
Edu	Years of education (year)
Gender	1 if male, 0 otherwise
Non-farm	1 if engaged in a non-farm job, 0 otherwise
Household characteristics	
Others_non-farm	Number of household members engaged in non-farm 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 household accessing to internet in the same village (%)
Neighbor smartphone	Percentage of other sampled adult owning smartphones in the same village (%)
Telecom	1 if there has at least one business office established by the China Mobile or China Unicom in the village, 0 otherwise
	Panel B: Variables for E-commerce adoption
E-commerce	1 if the fruits producer sells apple, peach, walnut or kiwifruit online
Individual characteristics	
Age	Age of the sale decision-maker (year)
Edu	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_non-farm	Number of members engage in non-farm 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
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 [a], 0 otherwise

Note: [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 shows the descriptive results of ICTs adoption at the household level. Generally, there are significant differences in the observed characteristics between the adopters and non-adopters of computer and internet. On average, those household heads adopting computer and internet are younger, with more years of schooling, having experience in working in the non-farm sectors. Also, households with more family members, especially members engaging in non-agricultural jobs, and cultivating more farmland show a higher proportion of adopting ICTs. Moreover, the villages' infrastructure and the neighborhood ICTs adoptions are positively correlated with the households' adoptions of computer and internet.

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

Variables	Mean (Std. Dev.)	Computer (Mean=0.28, Std. Dev.=0.45)			Internet (Mean=0.74, Std. Dev.=0.44)		
		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***
	(10.29)	(9.60)	(10.28)		(10.11)	(9.57)	
Edu	6.79	7.86	6.37	1.49***	7.10	5.85	1.25***
	(3.23)	(3.17)	(3.16)		(3.14)	(3.32)	
Gender	0.98	0.99	0.98	0.01***	0.99	0.97	0.02***
	(0.13)	(0.11)	(0.14)		(0.12)	(0.17)	
Nonfarm	0.30	0.44	0.25	0.19***	0.36	0.12	0.24***
	(0.46)	(0.50)	(0.43)		(0.48)	(0.32)	
Household characteristics							
Others_nonfarm	0.92	0.95	0.61	0.34***	0.93	0.35	0.58***
	(1.06)	(0.99)	(0.90)		(0.97)	(0.73)	
Farmland	0.33	0.37	0.29	0.08***	0.35	0.30	0.05*
	(0.67)	(0.80)	(0.54)		(0.67)	(0.47)	
Household size	4.25	4.27	3.58	0.69***	4.86	3.29	1.57***
	(1.82)	(1.68)	(1.75)		(1.72)	(1.73)	
Village characteristics							
Neighbor computer	31.01	43.25	25.66	17.59***	32.03	26.35	5.68***
	(0.20)	(18.75)	(17.75)		(19.91)	(18.38)	
Neighbor internet	75.78	79.56	74.17	5.39***	81.04	60.01	21.03***
	(0.21)	(19.31)	(21.24)		(17.92)	(20.93)	
Neighbor smartphone	68.72	71.92	66.82	5.10***	70.12	62.77	7.35***
	(0.12)	(11.21)	(12.37)		(11.63)	(12.47)	
Telecom	0.20	0.23	0.18	0.05***	0.20	0.18	0.02
	(0.40)	(0.42)	(0.39)		(0.40)	(0.39)	

Notes: Samples=13570. *, **, and *** indicate p<0.10, p<0.05, p<0.01, respectively.

Table 3 shows the differences in the characteristics between smartphone adopters and non-adopters. Similar to those found in Table 2 on using computer and access to internet by household, there exist significant differences of all the characteristics except Telecome between smartphone adopters and non-adopters. Specifically, the individuals with smartphone are younger, better educated and more employed in non-farm sectors than those without smartphone. Meanwhile, the individuals with more non-farm job, more land, and more family members also tend to have a smartphone. Moreover, the neighborhood effect are potential enabling factors for individual's usage of smartphones.

Table 3. Descriptive statistics of the smartphone adoption at the individual level

Variables	Mean	Smartphone (Mean=0.70, Std. Dev.=0.46)		
	(Std. Dev.)	Yes	No	T-test
Individual characteristics				
Age	45.62	39.55	59.77	-20.22^{***}
	(15.76)	(13.19)	(11.64)	
Edu	7.55	8.67	4.92	3.75^{***}
	(3.90)	(3.54)	(3.39)	
Gender	0.52	0.55	0.46	0.09^{***}
	(0.50)	(0.50)	(0.50)	
Nonfarm	0.42	0.56	0.09	0.47^{***}
	(0.49)	(0.50)	(0.28)	
Household characteristics				
Others_nonfarm	0.92	1.06	0.59	0.47^{***}
	(1.06)	(1.10)	(0.88)	
Farmland	0.33	0.34	0.31	0.03^{***}
	(0.67)	(0.70)	(0.57)	
Household size	4.25	4.36	4.00	0.36^{***}
	(1.82)	(1.79)	(1.88)	
Village characteristics				
Neighbor computer	31.01	32.27	28.06	4.21^{***}
	(0.20)	(19.85)	(19.16)	
Neighbor internet	75.78	77.49	71.79	5.70^{***}
	(0.21)	(20.22)	(22.03)	
Neighbor smartphone	68.72	70.65	64.21	6.44^{***}
	(0.12)	(11.21)	(11.92)	
Telecom	0.20	0.21	0.18	0.03
	(0.40)	(0.40)	(0.39)	

Notes: Samples=45933. *, **, and *** indicate p<0.10, p<0.05, p<0.01, respectively

Tables A1 and A2 in the Appendix show more details of the relationships between three major ICTs applications and the characteristics of individuals, households and villages. The results further raise the concern on the inequity or inclusive of ICTs adoptions 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 fruit producers using e-commerce to sell their products. Our survey samples have nearly half of fruit producers (49%) engaged in e-commerce in 2015-2019. Through comparing the mean of each variable between e-commerce users and non-users in Table 4, the results show that the decision makers who are younger and female and have more years of schooling, the training in e-commerce, the smartphone and the non-farm job tend to have more likely using e-commerce to sell their fruits. Also, more family members working on non-farm job, more farmland, being a member of farmer cooperative, and more relative (within 3 generations) in the field of agricultural business are more inclined to be e-commerce users. Moreover, the local logistic conditions and locations also contribute to the differences in fruit producers' decision on selling their fruits online.

Table 4. Descriptive statistics of the e-commerce adoption

Variables	Mean (Std. Dev.)	E-commerce (Mean=0.49, Std. Dev.=0.50)		
		Yes	No	T-test
Decision-maker characteristics				
Age	48.46	45.19	51.64	-6.45^{***}
	(10.51)	(9.55)	(10.46)	
Edu	9.39	10.19	8.62	1.57^{***}
	(2.90)	(3.01)	(2.57)	
Gender	0.84	0.80	0.88	-0.08^{***}
	(0.37)	(0.40)	(0.32)	
Train	0.31	0.50	0.14	0.36^{***}
	(0.46)	(0.50)	(0.34)	
Smartphone	0.83	0.95	0.71	0.24^{***}
	(0.38)	(0.23)	(0.45)	
Nonfarm	0.49	0.61	0.39	0.22^{***}
	(0.49)	(0.49)	(0.49)	
Household characteristics				
Others_nonfarm	1.01	1.15	0.87	0.29^{***}
	(0.92)	(0.97)	(0.85)	
Farmland	0.53	0.72	0.35	0.37^{***}
	(0.85)	(1.13)	(0.35)	
Cooperation	0.30	0.40	0.21	0.19^{***}
	(0.46)	(0.49)	(0.40)	
Relative	1.82	2.14	1.51	0.63^{***}
	(3.37)	(3.34)	(3.38)	
Village characteristics				
Express	0.18	0.23	0.13	0.10^{***}
	(0.38)	(0.42)	(0.34)	
Distance	8.27	7.01	9.49	-2.48^{***}
	(7.53)	(6.04)	(8.57)	
Interaction				
Child	0.20	0.23	0.18	0.05^{**}
	(0.40)	(0.42)	(0.38)	

Notes: Samples=1090. *, **, and *** indicate p<0.10, p<0.05, p<0.01, respectively.

The survey results confirm the importance of intergenerational support from the decision maker's children on whether to engage in e-commerce. Specifically, for some fruit producers using e-commerce to sell their products, the online sales are not completely implemented by the sale decision-makers themselves. In often cases, the children of decision-makers, in particular those with old age and less schooling, act as the actual operator or offer help in doing business online. To measure this effect, we construct a variable named as Child that equals 1 if any child of the decision maker has a job with a high level of social network connection, 0 otherwise (see the note under Table 1). Our statistics shown in the last row of Table 4 indicate 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, the fruit producers using e-commerce to sell their fruits have more percentage of children working in the above job (23%) than that of the households not using e-commerce (18%).

Table A3 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 with the descriptive analyses presented in Table 4.

4. Model specification and estimation

Follow a common approach on a household's or individual's decision on whether to adopt new technology, the decision depends on the utility the household or individual expects to derive from this adoption. The adoption occurs when the expected utility of using ICTs (U_{1i}) is greater than the utility without using ICTs (U_{0i}), i.e.,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 ICTs adoption exceeds the utility without adoption. While the utility difference cannot be directly observed, a household's or individual's propensity to adopt ICTs can be expressed in a linearized form as follows:

$$ICT_{ikt}^{*} = \beta_1 I_{it} + \beta_2 L_{it-1} + \beta_3 V_{it-1} + \varepsilon_{it} \quad (1)$$

$$ICT_{ikt} = 1[\ ICT_{ikt}^{*} \geq 0] \quad (2)$$

Where the subscript ICT_{ikt} represents the i^{th} household or individual adopts the k^{th} *ICT* (k=1 or 2 or 3, representing using computer or access to internet or having 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-1} is a vector of non-farm job of household head or individual and household characteristics in one-year lagged form; the household characteristics include the number of the other household members engaging in non-farm jobs, farmland, and household size. V_{it-1} is a vector of village characteristics in one-year lagged form, including the percentages of households having computer, access to internet, and whether having a telecom office in the village. 1[·] is an indicator function, denoting ICT_{ikt} =1 if $ICT_{ikt}^{*} \geq 0$; otherwise, $ICT_{ikt} = 0$. $\beta_1, \beta_2\ and\ \beta_3$ are the vector of parameters to be estimated. ε_{it} is a random error term, which is assumed to be normally distributed.

The logic 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 time-invariant factors that may affect the ICT adoptions, and year dummies can control yearly specific impact. For correcting the potential estimation errors caused by the different samples size among different provinces and overtime, 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 a adoption decision model as follow:

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

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 decision-maker, including age, gender, and education. L'_{it-1} is a vector in one-year lagged variables of having e-commerce training, smartphone and non-farm job of the decision-maker, and of number of non-decision-maker household members with non-farm jobs, farm land, being a member of farmer's professional cooperative and number of the relatives within three generations engaging in marketing business. V'_{it-1} is a vector of village characteristics in one-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 the 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 ICTs adoptions

Table 5 presents the estimation results of whether household having computer and internet access based on a logit model. To check the robust of estimation results, additional two alternative specifications in terms of whether considering the year effect and the village fixed effect are estimated: the columns (2) and (5) consider the year effect (a dummy for each year); and the columns (3) and (6) consider both year effect and the village fixed effect. Generally, the results are consistent among three alternative estimations. In the rest of discussions, we focus on the estimation results in the columns (3) and (6).

The estimation results provide strong evidence of the digital divide in terms of age and education. The estimated parameters for household head's age and education are statistically significant at 1% for all alternative specifications (rows 1 in Table 5). One-year increase of the household head's age reduces the probability of households using computers by 0.9% (column 3) and access to internet by 0.7% (column 6). One year more schooling of household head increases the probability of household using computer by 1.4% and access to internet by 0.9%. These results are consistent with the previous findings that the younger and higher educated farmers are more likely to adopt ICTs (e.g., Aker and Mbiti, 2010; Al-Hassan et al., 2013 and Leng et al., 2020).

Table 5 also shows that non-farm employment, farm size and household size have significantly affected the uses of computer and internet by rural households. The non-farm employment has positive effect on using ICTs (row 5), which can be attributed to the benefits stemming from non-farm employment such as improvement of human capital, enhancement of income and also extension of social network (Ma et al., 2018). However, it is interesting to note that the non-farm employment of household head does not affect the household using computer and internet (row 4). While this result may differ from the general positive impact findings in the literature, this may reveal that rural household's using computer and internet is mainly driven by their children after controlling for the household head's age and education. Additionally, those households with more cultivated land are more likely to have computer and internet access. This may be due to the fact that farmers operating more land have stronger initiative to improve the efficiency of agricultural production through good use of ICTs (Aker, 2011).

Table 5. Estimation results of households having computer and access to internet.

	Computer			Access to internet		
	(1)	(2)	(3)	(4)	(5)	(6)
Household head characteristics						
Age $_{it}$	-0.007***	-0.007***	-0.009***	-0.006***	-0.007***	-0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Edu $_{it}$	0.012***	0.012***	0.014***	0.009***	0.008***	0.009***
	(0.002)	(0.002)	(0.003)	(0.001)	(0.001)	(0.001)
Gender $_{it}$	-0.102	-0.104	-0.118	-0.009	-0.012	-0.014
	(0.104)	(0.103)	(0.116)	(0.010)	(0.010)	(0.010)
Nonfarm $_{it-1}$	-0.033	-0.037	-0.048	0.032	0.019	0.016
	(0.033)	(0.034)	(0.042)	(0.019)	(0.019)	(0.019)
Household characteristics						
Others_nonfarm $_{it-1}$	0.040***	0.042***	0.042***	0.050***	0.051***	0.064***
	(0.005)	(0.005)	(0.004)	(0.003)	(0.003)	(0.003)
Farmland $_{it-1}$	0.033***	0.033***	0.035***	0.019***	0.017***	0.035***
	(0.006)	(0.006)	(0.008)	(0.003)	(0.002)	(0.005)
Household size $_{it-1}$	0.005	0.005	0.017**	0.021***	0.022***	0.018***
	(0.005)	(0.005)	(0.007)	(0.004)	(0.004)	(0.005)
Village characteristics						
Neighbor computer $_{it-1}$	0.007***	0.008***	0.004***	-0.000	-0.000	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Neighbor internet $_{it-1}$	0.000	-0.000	0.001	0.006***	0.006***	0.004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Telecom $_{it-1}$	0.008	0.006	0.003	0.015**	0.015**	0.038***
	(0.017)	(0.016)	(0.008)	(0.005)	(0.005)	(0.010)
Village fixed effect	No	No	Yes	No	No	Yes
Year dummies	No	Yes	Yes	No	Yes	Yes

Notes: Samples =13570. The estimated parameters are marginal effects and the standard errors are in parentheses. *, **, and *** indicate p<0.10, p<0.05, p<0.01, respectively.

The estimated parameters for the intensive of using computer (or internet) by the other households in the village has significantly positive effect on the household's using computer (or internet) (rows 8 and 9). These results provide a strong evidence for the existence of neighborhood effects and social learning relating to the adoption of ICTs among rural households. Finally, the effect of telecom on households' access to internet is significantly positive. This indicates that the equipment of mobile infrastructure in the villages lays the foundation for the diffusion of internet in rural areas.

Table 6 reports the estimation results of individual having smartphone. Similar to the findings of households' usage of computer and internet, age and education of individuals, non-farm employment of other family members and farmland of the household, percentage of having computer and smartphone within the whole village all have significant effect on individuals' usage of smartphone. In addition, the differences of individuals using smartphone between male and female and non-farm experience are also confirmed. Specifically, on average, the probability of male using smartphone is 5.6% higher than that of female (row 3). In comparison to those who do not engage in non-farm jobs, employed in non-farm sectors leads to 8% to 9% increase in having smartphone (row 4).

Table 6. Estimation results of individuals having smartphone.

	(1)	(2)	(3)	(4)
Individual characteristics				
Age $_{it}$	-0.011***	-0.011***	-0.012***	-0.012***
	(0.000)	(0.000)	(0.000)	(0.000)
Edu $_{it}$	0.015***	0.014***	0.015***	0.015***
	(0.001)	(0.001)	(0.001)	(0.001)
Gender $_{it}$	0.054***	0.055***	0.055***	0.056***
	(0.008)	(0.008)	(0.008)	(0.008)
Nonfarm $_{it-1}$	0.096***	0.089***	0.083***	0.080***
	(0.002)	(0.002)	(0.002)	(0.002)
Household characteristics				
Others_nonfarm $_{it-1}$	0.006*	0.007**	0.015***	0.015***
	(0.003)	(0.003)	(0.004)	(0.004)
Farmland $_{it-1}$	0.008***	0.009***	0.009***	0.010***
	(0.002)	(0.001)	(0.002)	(0.002)
Household size $_{it-1}$	-0.006*	-0.006*	-0.008	-0.008
	(0.003)	(0.003)	(0.005)	(0.005)
Village characteristics				
Neighbor computer $_{it-1}$	0.000	0.000	0.001***	0.001**
	(0.000)	(0.000)	(0.000)	(0.000)
Neighbor smartphone $_{it-1}$	0.005***	0.005***	0.008***	0.005***
	(0.000)	(0.000)	(0.001)	(0.000)
Telecom $_{it-1}$	0.014***	0.013***	0.010***	0.008**
	(0.004)	(0.004)	(0.002)	(0.003)
Village fixed effect	No	No	Yes	Yes
Year dummies	No	Yes	No	Yes

Notes: Samples=45,933. The estimated parameters are marginal effects and the standard errors are in parentheses. *, **, and *** indicate p<0.10, p<0.05, p<0.01, respectively.

5.2 Enabling and constraint factors affecting using e-commerce to sell fruits

On whether the fruit producers using e-commerce to sell their products, to check the robust of results, we estimated equation (3) with the following three sets of alternative regressions: 1) estimating models 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 A4); 2) estimating models 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 characteristics that do not change over time (Table 7); and 3) estimating models that considering the role of fruit sale decision-maker's children with the village fixed effect (Table 8).

The estimation results presented in Table A4 and Table 7 are generally consistent for nearly all variables except for the estimated parameters for two village characteristics. Without using the village fixed effect estimation, we found that the presence of a post office in the village positively correlates with households' selling fruits through e-commerce, while the distance to the nearest agricultural market negatively associates with using e-commerce to sell fruits. Due to the requirements for the timeliness of sales for most agricultural products, 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 in the villages or the difficulties to efficiently obtain agricultural market information in the nearby area (Couture et al., 2021). The above relationship is particularly evidenced in the post office (*Express*) in apple equation (column 2, Table A4) and the distance to the nearest agricultural market (*Distance*) in both apple and walnut equations (columns 2 and 4, Table A4). 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 7 with the village fixed effect estimation.

The estimation results also show a strong e-commerce divide among farmers (Table 7). For example, the estimated parameter for age of decision-maker is significant and negative for whole sample (column 1, Table 7) and for three of four products (apple, peach and walnut, columns 2-4). One-year increase in age leads to a 0.6% decline in the probability of fruit producers to sell their fruits online for whole sample, and about 0.8% to 0.9% for apple, walnut and peach (row 1). The years of schooling also has a significant and positive effect on farmers' participation in e-commerce for whole sample, and for walnut and kiwifruit (row 2). For one year increase of schooling of decision-maker, the probability of fruit producers to engage in e-commerce increases by 1.6% for average of all four fruits examined (row 2). When the models are estimated by each fruit, the significant effect is found only in walnut and kiwifruit, which may be due to the fact that the size of sample by product is not large enough to have more efficient estimation. Younger and more educated farmers are more likely to sell their products through e-commerce, which is also in line with the previous studies (Kabango & Asa, 2015; Luo & Niu, 2019). Interestingly, similar to the finding on having a computer or access to internet, we find that the use of e-commerce to sell product is not bias in gender (row 3).

A decision-maker attended any e-commerce training and had a smartphone are significantly and positively associated with his/her to use online sale (rows 4 and 5, Table 7). Undoubtedly, the specialized e-commerce training provided by the local government is beneficial for farmers to quickly understand and 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 sale.

Table 7. Estimation results of fruit producers using e-commerce: with village fixed effect

	Full sample	Apple	Peach	Walnut	Kiwifruit
	(1)	(2)	(3)	(4)	(5)
Decision maker characteristics					
Age $_{it}$	-0.006***	-0.008*	-0.009**	-0.008***	-0.004
	(0.002)	(0.004)	(0.004)	(0.002)	(0.003)
Edu $_{it}$	0.016***	-0.018	0.009	0.017**	0.022***
	(0.004)	(0.012)	(0.010)	(0.008)	(0.007)
Gender $_{it}$	-0.005	-0.117	0.056	0.026	0.033
	(0.031)	(0.079)	(0.068)	(0.056)	(0.069)
Train $_{it-1}$	0.152***	0.171***	0.151**	0.239***	-0.020
	(0.026)	(0.052)	(0.059)	(0.049)	(0.059)
Smartphone $_{it-1}$	0.131***	0.227***	0.151*	0.043	0.093*
	(0.032)	(0.061)	(0.090)	(0.071)	(0.055)
Nonfarm $_{it-1}$	0.058**	-0.020	0.161***	0.008	0.079
	(0.027)	(0.058)	(0.047)	(0.061)	(0.053)
Household characteristics					
Others_nonfarm $_{it-1}$	0.081***	0.166***	0.077**	0.022	0.062***
	(0.014)	(0.031)	(0.038)	(0.027)	(0.022)
Farmland $_{it-1}$	0.068***	0.015	0.147***	-0.027	0.066***
	(0.022)	(0.037)	(0.056)	(0.040)	(0.025)
Cooperation $_{it-1}$	0.056*	0.133**	0.131*	-0.077	0.006
	(0.031)	(0.064)	(0.076)	(0.072)	(0.052)
Relative $_{it-1}$	0.007*	0.008	-0.005	0.013***	0.001
	(0.004)	(0.008)	(0.027)	(0.004)	(0.006)
Village characteristics					
Express $_{it-1}$	-0.094	0.022	-0.105	-0.137	-0.047
	(0.061)	(0.118)	(0.129)	(0.125)	(0.146)
Distance $_{it-1}$	-0.003	0.029	0.023	-0.008	-0.004
	(0.005)	(0.023)	(0.045)	(0.025)	(0.006)
Year dummies	Yes	Yes	Yes	Yes	Yes
Samples	1,090	243	235	362	250

Notes: The estimated parameters are marginal effects and the standard errors are in parentheses. *, **, and *** indicate p<0.10, p<0.05, p<0.01, respectively.

The positive impacts of decision-makers' non-farm employment on using e-commerce is evidenced in full sample and statistically significant in peach but not in the other three fruits (row 6, Table 7). The general positive impact result is consistent with the previous studies (e.g., Liu et al., 2021). Insignificant impacts based on the regression by product may be due to the following reasons in addition to the small size of sample. On one hand, non-farm employment is helpful for broadening farmers' horizon, expanding their social network, and thereby may enhance their acceptance of new technologies. On the other hand, the decision-maker's non-farm employment may have negative effect on using e-commerce because the online sale is labor intensive business and affects his/her non-farm work (Li et al., 2021). Moreover, in contrast to apple and walnut with relatively more durable freshness, the perishable peach has a shorter sale period, which tends to have less effect on the decision-maker's non-farm work.

The results also demonstrate that farms with better resource endowments and wider social networks are more inclined to engage in e-commerce to sell their products (rows 7 to 10, Table 7). Specifically, fruit producers with more family members employed in the non-farm sector and larger farm size show a stronger tendency to selling their fruits online (rows 7 and 8). Moreover, being a member of farmers' professional cooperative and the number of relatives within three generations operating marketing business, which directly measure the household's social network connection, both have positive impact on 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). Interestingly, the positive impact of more relatives is only confirmed in the walnut equation (row 10), which needs further investigation in the future.

The results presented in Table 8 further considers 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 sale decision-maker has any child having a job with a high level of social network connection. Although the impact of intergenerational support on the adoption of new technologies has been discussed in the existing literature (Liikanen, 2004; Freeman et al., 2020), little is known about the potential supporting role of sale decision-maker's children in his/her involvement in online sales.

As shown in column (1) of Table 8, the estimation parameters of interaction items (*Age* * *Child*, *Edu* * *Child*) are positively and negatively significant at 1% and 5% levels, respectively (rows 2 and 4). For the fruit producers without any child having a job with a high level of social network connection (farm A), age with one year more can lower the farm A's probability of using e-commerce by 0.8% (row 1), but for the fruit producers with their children's help (farm B), the corresponding impact is 0.1% only (-0.8%+0.7%) (rows 1 and 2). Similar, for the farm A, one year less schooling can lower its probability of using e-commerce by 1.9% (row 3), but the farm A, this impact is more than offset by the help from children (-1.9% + 2.3%=0.4%). These results suggests that the constraints for aged and less schooling fruit producer to engage in e-commerce can be significantly eased with the help of their children. A reasonable explanation is that having children working with a high-level social network connection would help to implement online sales through making good use of the advantages of children in broad access to market information, and extension of social network for products online sales.

Table 8. Estimation results of fruit producers using e-commerce with the village fixed and year fixed effects: considering the role of decision-maker's children.

	Full sample	Apple	Peach	Walnut	Kiwifruit
	(1)	(2)	(3)	(4)	(5)
Decision-maker characteristics					
Age $_{it}$	-0.008***	-0.009**	-0.009**	-0.014***	-0.005*
	(0.002)	(0.004)	(0.004)	(0.002)	(0.003)
Age $_{it}$ * *Child* $_{it}$	0.007***	0.018***	-0.005	0.006***	0.010***
	(0.001)	(0.006)	(0.005)	(0.002)	(0.002)
Edu $_{it}$	0.019***	-0.011	0.003	0.007	0.027***
	(0.005)	(0.012)	(0.011)	(0.007)	(0.008)
Edu $_{it}$ * *Child* $_{it}$	-0.023**	-0.090***	0.020	-0.006	-0.038**
	(0.009)	(0.034)	(0.035)	(0.012)	(0.016)
Gender $_{it}$	-0.009	-0.079	0.064	-0.017	0.028
	(0.031)	(0.076)	(0.067)	(0.047)	(0.062)
Train $_{it-1}$	0.135***	0.183***	0.195***	0.211***	-0.057
	(0.027)	(0.051)	(0.057)	(0.049)	(0.051)
Smartphone $_{it-1}$	0.154***	0.272***	0.155**	0.043	0.142***
	(0.032)	(0.061)	(0.074)	(0.056)	(0.053)
Nonfarm $_{it-1}$	0.072***	-0.026	0.158***	0.042	0.102*
	(0.028)	(0.061)	(0.046)	(0.054)	(0.054)
Household characteristics					
Others_nonfarm $_{it-1}$	0.048***	0.148***	0.098**	-0.019	-0.003
	(0.015)	(0.032)	(0.039)	(0.024)	(0.024)
Farmland $_{it-1}$	0.067***	0.012	0.149**	-0.047	0.058***
	(0.022)	(0.034)	(0.058)	(0.032)	(0.021)
Cooperation $_{it-1}$	0.060*	0.134**	0.133*	-0.024	-0.021
	(0.031)	(0.059)	(0.070)	(0.074)	(0.051)
Relative $_{it-1}$	0.007**	0.011	-0.003	0.011***	-0.004
	(0.004)	(0.008)	(0.026)	(0.003)	(0.004)
Village characteristics					
Express $_{it-1}$	-0.101	0.022	-0.070	-0.045	-0.080
	(0.061)	(0.109)	(0.121)	(0.099)	(0.154)
Distance $_{it-1}$	-0.005	0.021	0.021	-0.006	-0.006
	(0.004)	(0.021)	(0.045)	(0.024)	(0.006)
Samples	1,090	243	235	362	250

Notes: The estimated parameters are marginal effects and the standard errors are in parentheses. *, **, and *** indicate p<0.10, p<0.05, p<0.01, respectively.

The columns (2) to (5) of Table 8 present the results by apple, peach, walnut, and kiwifruit. Specifically, the positive role of able children to relieve the constraints of their parents engaging e-commerce is particularly evidenced in apple, walnut and kiwifruit (row 2). Meanwhile, this positive effect to break the constraints of less schooling parents engaging e-commerce is also evidenced in apple and kiwifruit (row 4).

6. Concluding remarks

Using two sets of household survey datasets in 2015-2019, we document the trends of ICTs application and e-commerce adoption to sell fruits in the past five years in rural China, empirically test the enabling and constraint factors of farmers' using ICTs and e-commerce, and discuss the inequity issues of digital technology in general and the computer use, access to internet and using e-commerce to sell farm products in particular.

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

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

This study also provides a strong evidence that 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 schooling farmers to participate e-commerce business. However, there are also many aged and less schooling farmers without this kind of typical support from their children. They are much behind in using e-commerce than all other producers now, and this divide will be enlarged as they will get older over time.

The results of this study have several policy implications. First, while 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 in general and using ICTs and e-commerce in particular, new inequality will occur in rural areas in the digital era. Second, more supports should be provided to the disadvantaged rural households and farmers through skill training, social network improvement, farm size expansion of the current smallholders, farmers' cooperative development and other capacity building programs. Particular attention should be given to the aged and less schooling farmers and farmers in the less developed regions. Last but not the least, investment in ICTs' infrastructure and enhancing storing facilities and logistics for e-commerce in rural, particularly in less developed rural areas, are essential to advance equitable likelihood in the course of ICTs diffusion and e-commerce development.

Appendix

Table A1. Characteristics of household head, household, village and percentages of household using computer and internet in 10 provinces in 2015-2019

	Obs.	Computer (%)			Internet (%)		
	Full sample	2015-2019	2015	2019	2015-2019	2015	2019
Total	13,570	30	28	31	70	55	83
Household head characteristics							
By age							
16-30	107	48	47	44	89	82	89
31-45	1,840	40	38	43	84	71	96
46-60	6,210	36	33	39	77	60	94
Above 60	5,413	19	16	21	56	38	71
By education							
Elementary school or below	6,277	22	20	24	62	47	75
Junior middle school	5,562	34	32	35	76	60	89
High school or above	1,731	46	43	47	79	64	93
By gender							
Male	13,367	30	28	31	70	55	83
Female	203	20	19	23	52	42	64
Household characteristics							
By others_nonfarm							
0	7,982	23	24	22	60	43	76
1	3,556	39	35	42	83	72	92
2 and above	2,032	42	36	44	86	74	95
By farmland							
0.3 hectare or below	8,600	29	27	31	72	57	84
0.3-1 hectare	3,839	28	26	30	64	49	80
Above 1 hectare	1,131	42	45	38	75	58	90
By household size							
2 or below	3,561	15	15	15	53	38	67
2-4	5,653	35	33	36	75	59	90
Above 4	4,356	35	32	37	79	62	88
Village characteristics							
By neighbor computer							
20 percent or below	4,364	11	9	10	63	49	78
20-40 percent	4,817	28	27	27	70	54	82
Above 40 percent	4,389	51	51	52	76	61	89
By neighbor internet							
50 percent or below	4,568	24	25	6	48	41	49
50-70 percent	3,154	30	31	22	69	63	62
Above 70 percent	5,848	34	32	34	87	80	89

Table A2. Characteristics of individual, household, village and percentages of individual using smartphone in 10 provinces in 2015-2019

	Obs.	Smartphone (%)		
	Full sample	2015-2019	2015	2019
Total	45,933	68	63	71
Individual characteristics				
By age				
16-30	10,216	95	89	98
31-45	11,560	92	85	97
46-60	13,444	65	51	77
Above 60	10,713	21	14	25
By education				
Elementary school or below	17,804	45	39	48
Junior middle school	18,993	79	73	82
High school or above	9,136	91	85	94
By gender				
Male	23,933	71	65	74
Female	21,940	65	60	67
Household characteristics				
By others_nonfarm				
0	22,706	59	55	60
1	13,389	74	69	76
2 and above	9,838	82	76	85
By farmland				
0.3 hectare or below	28,793	69	63	71
0.3-1 hectare	13,202	65	60	68
Above 1 hectare	3,938	74	66	78
By household size				
2 or below	6,702	48	43	51
2-4	19,441	72	66	75
Above 4	19,790	71	66	74
Village characteristics				
By neighbor computer				
20 percent or below	14,313	64	59	66
20-40 percent	16,208	68	63	70
Above 40 percent	15,412	72	66	76
By neighbor smartphone				
60 percent or below	15,520	57	54	53
60-70 percent	15,598	69	68	67
Above 70 percent	14,824	80	77	79

Table A3. Characteristics of decision-maker, household, village and percentages of household engaging in e-commerce in Zhejiang and Shandong

	Obs.	E-commerce (%)		
	Full sample	2015-2019	2015	2019
Total	1,090	49	31	59
Decision-maker characteristics				
By age				
16-30	66	82	50	98
31-45	309	60	34	79
46-60	500	47	25	58
Above 60	156	19	13	32
By education				
Elementary school or below	212	31	13	49
Junior middle school	490	45	27	55
High school or above	388	64	43	70
By gender				
Male	916	47	30	57
Female	174	63	36	70
Household characteristics				
By others_nonfarm				
0	247	34	13	49
1	291	43	24	51
2 and above	552	59	44	66
By farmland				
0.3 hectare or below	541	44	28	54
0.3-1 hectare	462	49	29	59
Above 1 hectare	87	86	56	94
By relative				
0	531	41	22	52
1-3	389	56	37	64
Above 3	170	60	44	71
Village characteristics				
By distance				
3 kilometers or below	244	53	32	67
3-10 kilometers	631	50	30	63
Above 10 kilometers	215	43	31	44
Interaction				
By child				
0	869	48	28	57
1	221	55	41	65

Table A4. Estimation results of fruit producers using e-commerce: without village fixed effect

	Full sample	Apple	Peach	Walnut	Kiwifruit
	(1)	(2)	(3)	(4)	(5)
Decision-maker characteristics					
Age $_{it}$	-0.009***	-0.006	-0.010**	-0.011***	-0.005
	(0.002)	(0.005)	(0.004)	(0.002)	(0.003)
Edu $_{it}$	0.010**	-0.010	0.009	0.020**	0.018***
	(0.005)	(0.012)	(0.010)	(0.008)	(0.006)
Gender $_{it}$	-0.031	-0.167**	0.081	-0.018	0.011
	(0.034)	(0.082)	(0.067)	(0.051)	(0.066)
Train $_{it-1}$	0.204***	0.179***	0.178***	0.274***	-0.004
	(0.026)	(0.050)	(0.057)	(0.037)	(0.062)
Smartphone $_{it-1}$	0.103***	0.204**	0.144	0.019	0.079
	(0.035)	(0.080)	(0.100)	(0.076)	(0.054)
Non-farm $_{it-1}$	0.073***	-0.019	0.156***	0.018	0.098*
	(0.026)	(0.066)	(0.049)	(0.063)	(0.056)
Household characteristics					
Others_nonfarm $_{it-1}$	0.108***	0.144***	0.083**	0.053*	0.070***
	(0.014)	(0.033)	(0.036)	(0.027)	(0.019)
Farmland $_{it-1}$	0.125***	0.104*	0.173***	-0.088	0.037
	(0.028)	(0.060)	(0.067)	(0.071)	(0.047)
Cooperation $_{it-1}$	0.132***	0.097*	0.171***	-0.002	0.065**
	(0.027)	(0.055)	(0.054)	(0.041)	(0.028)
Relative $_{it-1}$	0.007*	0.007	-0.007	0.018***	-0.000
	(0.004)	(0.008)	(0.026)	(0.004)	(0.007)
Village characteristics					
Express $_{it-1}$	0.156***	0.166**	0.009	-0.080	-0.193
	(0.041)	(0.083)	(0.078)	(0.081)	(0.132)
Distance $_{it-1}$	-0.005***	-0.031***	-0.008	-0.014***	0.000
	(0.002)	(0.010)	(0.017)	(0.004)	(0.005)
Year dummies	Yes	Yes	Yes	Yes	Yes
Samples	1,090	243	235	362	250

Notes: The estimated parameters are marginal effects and the standard errors are in parentheses. *, **, and *** indicate p<0.10, p<0.05, p<0.01, respectively.

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