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Impact of smartphone use on production outsourcing: evidence from litchi farming in southern China

RESEARCH ARTICLE

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Abstract

There is a great deal of evidence suggesting that information and communication technology (ICT) and agricultural production outsourcing can improve farm productivity and farmers' welfare. However, less is known about the relationship between modern ICT use and agricultural production outsourcing. Drawing upon a survey of 855 litchi growers from southern China, this study estimates the effect of smartphone use on farmers' decisions regarding agricultural production outsourcing. A novel genetic matching method is employed to mitigate the selection bias associated with self-selected smartphone use. Our result confirms the positive role of smartphone use in increasing the number of production tasks outsourced by litchi growers. Moreover, smartphone users are more likely to outsource both labor-intensive and technology-intensive tasks than nonusers. In addition, the treatment effect of smartphone use varies with each specific litchi production task. Our findings highlight the importance of improving smartphone adoption among farmers to promote agricultural production outsourcing.

Keywords: smartphone, agricultural production outsourcing, genetic matching, litchi growers, rural China
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1. Introduction

China has made great achievements in economic development since the introduction of the reform and opening-up policy in 1978. In 2020, the gross domestic product of China was 14,722.73 billion US dollars according to the World Bank.[1] In the same year, the Seventh National Population Census of China revealed that the urbanization rate reached 63.89%.[2] Rapid urbanization and industrialization have triggered rural-urban labor migration and environmental degradation, which create pressure on the sustainability of small farms and Chinese food security (Liu *et al.,* 2010; Su *et al.,* 2011; Wang *et al.,* 2015).

There is a great deal of evidence suggesting that smartphone use and agricultural production outsourcing have the potential to overcome the disadvantages of the current Chinese farming system, such as small-scale farming, aging farmers, labor shortages, lack of machine ownership, and low modern technology adoption rate. Agricultural production outsourcing is expected to reduce smallholder farmers' input costs and increase output profits via the division of labor and economies of scale. By outsourcing agricultural production tasks to individuals or organizations with machine ownership and relevant skills, smallholder farmers can reduce production costs, enhance productivity, and enjoy more leisure time (Deng *et al.,* 2020; Mi *et al.,* 2020; Zhang *et al.,* 2018). The use of information and communication technology (ICT) can alleviate information asymmetry and reduce transaction costs in the agricultural sector (Aker, 2011; Aker *et al.,* 2016; Jensen, 2010). Recently, Chinese farmers have gradually adopted smart devices (especially smartphones) and benefited from the use of these modern ICT tools (Ma *et al.,* 2018; Nie *et al.,* 2020; Zheng and Ma, 2021b). Smartphone use enables rural households to connect to the internet without access to landline networks. In addition to basic functions such as making phone calls and sending text messages, smartphone users are able to take pictures, share videos, and customize their extension services using software applications (apps). Given these benefits of smartphone use, understanding the relationship between smartphone use and agricultural production outsourcing could provide evidence to effectively upscale the significant contributions of these two objects to improve rural sustainable development in developing countries.

The primary objective of this study is, therefore, to investigate the effect of smartphone use on agricultural production outsourcing. Our main finding is that smartphone use positively affects farmers' decisions regarding agricultural production outsourcing. Moreover, we divide the tasks into labor-intensive and technology-intensive groups and find positive effects of smartphone use on the number of labor- and technology-intensive tasks outsourced. In addition, the results suggest that the treatment effect of smartphone use varies with each specific production task. Our findings serve as a reference for the design of policies aiming to promote agricultural production outsourcing through the adoption of smartphones.

The contribution of this study is threefold. First, this study adds to the literature on the impact of ICT adoption on supporting sustainable agricultural production and rural development by estimating the effects of smartphone use on production outsourcing. There is extensive evidence that ICT use improves the welfare of smallholder farmers by raising income, diversifying income sources, smoothing consumption, and improving psychological health and food security (Beuermann, 2015; Leng *et al.,* 2020; Ma *et al.,* 2020a; Min *et al.,* 2020; Twumasi *et al.,* 2021; Zheng and Ma 2021a; Zhu *et al*., 2020a,b, 2021b). Mobile phone- and internet-using farmers can receive timely information, improve knowledge of advanced technologies and are more likely to adopt modern farming practices (Cai *et al.,* 2022; Campenhout *et al.,* 2021; Kiiza and Pederson, 2012; Larochelle *et al.,* 2019; Ogutu *et al.,* 2014; Shiferaw *et al.,* 2015). In rural China, ICT users adopt more sustainable agricultural practices (Ma and Wang, 2020) and are more willing to use e-commerce (Ma *et al.,* 2020b) than nonusers. Internet use improves farm technical efficiency (Zheng *et al.,* 2021; Zhu *et al.,* 2021a) and reduces pesticide use (Zhao *et al.,* 2021) and cropland abandonment (Deng *et al.,* 2019). However, to the best of our knowledge, no previous study has focused on the effect of smartphone use on agricultural production outsourcing.

[1] World Bank data: https://data.worldbank.org/indicator/NY.GDP.MKTP.CD?locations=CN
[2] Main data from the Seventh National Population Census of China: http://www.stats.gov.cn/english/PressRelease/202105/t20210510_1817185.html

Second, a dataset that covers 855 litchi growers from southern China is employed in this study. Southern China is an ideal setting because the vibrant nonagricultural economy provides plenty of off-farm work opportunities for rural households. Litchi is a traditional cash crop and is concentrated in southern China, in such areas as Guangdong Province, Guangxi Province, and Fujian Province. Litchi has a long growing season with labor-intensive tasks (e.g. weeding, irrigation, and harvesting) and technology-intensive tasks (e.g. pruning, girdling, and grafting). According to the Chinese National Litchi and Longan Industry Technology System (CNLLITS), the 2020 litchi output was approximately 2.554 million tons from 543,000 hectares of orchards. Similar to other Chinese agricultural sectors, the litchi industry is facing serious problems, such as aging farmers, peak season labor shortages, and small-scale farming, and there is a great demand for litchi production outsourcing services. Our findings can provide guidance to further promote litchi production outsourcing in southern China.

Third, we exploit a novel empirical approach named genetic matching. Matching is a commonly used approach for estimating the treatment effects in nonrandomized studies. In particular, the propensity score matching (PSM) approach has been widely adopted by researchers to tackle the selection bias issue associated with the self-selected use of ICT (Kiiza and Pederson, 2012; Ogutu *et al.,* 2014; Okello *et al.,* 2020). This approach relies on the correct treatment model specification. The PSM method matches the treatment and control groups based on the propensity score (Rosenbaum and Rubin, 1983). The distributions of observed covariates are assumed to be asymptotically the same after matching if the treatment equation is correctly specified. In practice, researchers face significant challenges in optimizing covariate balance because the correct model specification is generally unknown. However, previous studies rarely provide information regarding covariate balance, or they do not clearly state the modification of model specification. For example, Kiiza and Pederson (2012) and Okello *et al.* (2020) employed PSM to estimate the effects of ICT-based project participation on farmers' market participation and farm performance in rural Uganda and Kenya, respectively. Kiiza and Pederson (2012) fail to provide information on the covariate balance. The covariate balance results in Okello *et al.* (2020) suggest that the difference between the treatment and control groups was reduced after using PSM. However, there is less discussion on modifying the propensity score model specification. Genetic matching is able to overcome the weakness of PSM and yield a more reliable result using a search algorithm that iteratively checks and improves covariate balance (Diamond and Sekhon, 2013; Sekhon and Grieve, 2012). In other words, it does not require researchers to manually check the covariate balance and modify the model specification.

The remainder of this paper is structured as follows. The following section introduces the estimation strategy. Data and descriptive statistics are provided in Section 3. Section 4 presents and discusses our empirical results. We conclude this study in the final section.

2. Estimation strategy

In observational studies, there are many confounders that affect the treatment variable and interfere with the accurate identification of treatment effects (Cochran and Rubin, 1974). Matching assumes conditional independence on observables. PSM uses the propensity score as a balancing score to match treatment-control pairs. The matched pair will have a balancing covariate distribution if the propensity score model is correctly specified. In the balancing situation, the treatment variable is assumed to be uncorrelated with unobserved variables, and we thus can estimate the treatment effects by comparing the differences between the matched pairs. However, reality is often not the case. We cannot always specify a correct treatment model. In this regard, there is no guarantee that the overall covariate balance will be improved using PSM. Therefore, we decide to exploit genetic matching.

In this research, smartphone use is the treatment variable. Smartphone users and nonusers are considered the treatment and control groups, respectively. The average treatment effect for the treated (ATT) is given as:

$$ATT = E[Y(1) - Y(0)|T = 1,X] \tag{1}$$

where T indicates the smartphone use status. Y is the farmer's decision on agricultural production outsourcing. It is independent of T conditional on a covariance matrix of X.

Genetic matching matches the covariates associated with the outcome variable. Existing research suggests that farmers' decisions on outsourcing service use are determined by household characteristics (e.g. age, education, farm size), crop type, region, and specific task (Deng *et al.,* 2020; Ji *et al.,* 2017; Mi *et al.,* 2020; Sun *et al.,* 2018; Zhang *et al.,* 2018). In this regard, we include a range of household head- and farm-level variables, such as smartphone use, gender, age, education, health, training participation, family labor, party membership, cadre, share of litchi income, farm size, income, outsourcing service access, and outsourcing service provider in matrix X. The descriptions of the variables selected are presented in the next section.

Genetic matching is able to find the best measure from a range of distance metrics to optimize the postmatching covariate balance within a certain generation size. In particular, it creates an additional weight matrix (*W)* associated with each potential distance metric. The weight matrix (*W)* is used to document the relative importance of each covariate. It should be noted that the propensity score is also included as one of the covariates to realize the balance between the treatment and control groups. Essentially, genetic matching matches the treatment-control pairs by minimizing the Generalized Mahalanobis Distance (GMD) defined as follows (Diamond and Sekhon, 2013; Sekhon, 2011):

$$GMD\left(X_T, X_C, W\right) = \sqrt{\left(X_T - X_C\right)^T \left(S^{-1/2}\right)^T W \left(S^{-1/2}\right)\left(X_T - X_C\right)} \tag{2}$$

where W is the $k \times k$ positive definite weight matrix and S is the sample covariance matrix of X. X_T represents the covariates of the treatment group. X_C indicates the covariates of the control group. All elements of W are restricted to 0 except those down the main diagonal, which consists of k parameters that must be chosen.

Then, genetic matching automates the iterative process to check and improve the covariate balance by constantly updating the weight W toward a better overall covariate balance. Even though genetic matching does not require estimating the propensity score, the method will achieve better balance if a propensity score is incorporated (Sekhon, 2011). As expected, the overall covariate balance will be improved and converge asymptotically as the size of generation (i.e. times of weight W update) increases (Diamond and Sekhon, 2013). In this regard, we do not need to check the balance of covariates after matching due to the iterative process and optimal algorithm. This alleviates concerns about the mis specified problem of the treatment model. As genetic matching can be used with any arbitrary matching method (Diamond and Sekhon, 2013), we applied one-to-one matching with replacement in this study.

3. Data, variable definition, and descriptive statistics

3.1 Data

We used a household survey conducted from July 2020 to August 2020. A questionnaire that contains blocks of information, including household demographics, litchi production, and outsourcing behaviors, was applied for data collection. Before the survey, we modified the questionnaire based on a small-scale field test. The survey team members were graduate students selected from South China Agricultural University. They were trained on how to conduct interviews by the leading experts.

We applied a multistage sampling procedure to collect data. In the first stage, we selected the top two litchi-producing provinces in China (i.e. Guangdong Province and Guangxi Province). Four litchi-producing cities (Huizhou, Lianjiang, Maoming, and Yangjiang) in Guangdong Province and two cities (Qinzhou and Yulin) in Guangxi Province were selected in the second stage. In the third stage, we randomly selected one or two counties from each city. Within each selected county, two towns were randomly selected. In each town surveyed, we randomly selected approximately 25 farmers. As a result, we obtained 924 household samples. Finally, we selected 855 samples for this study after dropping 39 households that did not engage in litchi production and 30 samples due to incomplete information.

3.2 Variable definition and descriptive analysis

■ *Litchi production task description and outsourcing rate*

We found that litchi growers in surveyed areas outsource production tasks, including starter fertilizer application, regular fertilizer application, weeding, plant protection, irrigation, harvesting, pruning, fruit thinning, flower thinning, girdling, and grafting, to relatives and friends, large producers, agriculture cooperatives, and agriculture service companies. The definitions of these 11 litchi production tasks are shown in Table 1. Following the advice of CNLLITS experts, we define starter fertilizer application, regular fertilizer application, weeding, plant protection, irrigation, and harvesting as labor-intensive tasks. Currently, these six tasks require intensive labor investment. In contrast, pruning, fruit thinning, flower thinning, girdling, and grafting rely more on machines, knowledge, and skills. Thus, these five tasks are categorized as technology-intensive tasks.

The last column of Table 1 presents the outsourcing rate of each litchi production task. Among the 855 surveyed farmers, harvesting was the most outsourced task, with an outsourcing rate of 28.9%. Grafting and pruning are the second- and third-most outsourced tasks. The outsourcing rates are 15.7 and 12.0%, respectively. The outsourcing rates of the other eight tasks are lower than 10%. These results suggest that agricultural production outsourcing services have not been widely adopted by litchi farmers in southern China.

Table 1. Litchi production task description and outsourcing rate.

	Description and measurement	**Outsourcing rate**[1]
Labor-intensive tasks		
Starter fertilizer application	Apply starter fertilizer for a new production cycle. 1=outsourced, 0=otherwise	0.089 (0.285)
Regular fertilizer application	Apply regular fertilizer during litchi production cycle. 1=outsourced, 0=otherwise	0.081 (0.273)
Weeding	Remove unwanted plants in litchi orchard. 1=outsourced, 0=otherwise	0.075 (0.263)
Plant protection	Spray pesticide. 1=outsourced, 0=otherwise	0.085 (0.280)
Irrigation	Water litchi tree. 1=outsourced, 0=otherwise	0.042 (0.201)
Harvesting	Pick litchi. 1=outsourced, 0=otherwise	0.289 (0.454)
Technology-intensive tasks		
Pruning	Remove some litchi trees' branches, buds, or roots. 1=outsourced, 0=otherwise	0.120 (0.323)
Fruit thinning	Remove some litchi flowers. 1=outsourced, 0=otherwise	0.042 (0.201)
Flower thinning	Remove some litchi fruitlets. 1=outsourced, 0=otherwise	0.068 (0.252)
Girdling	Remove litchi trees' bark. 1=outsourced, 0=otherwise	0.008 (0.261)
Grafting	Connect scion and stock plants. 1=outsourced, 0=otherwise	0.157 (0.364)

[1] Mean and standard deviation (in parentheses).

■ *Characteristics of litchi farmers*

Table 2 presents the definition and summary of the treatment and covariate variables selected in this study. Our data show that 61% of surveyed farmers are smartphone users. This result is close to the Chinese rural internet penetration rate (55.9%) estimated by the China Internet Network Information Center in 2020.[3] Approximately 87% of household heads are male. The average age of the head of household is 57 years old. Approximately 64, 23 and 17% of household heads are training participants, party members, and village cadres, respectively. The average size of litchi orchards is approximately 1.3 ha. An average household generates 43% of its income from litchi farming. On average, the sample households have four members who are 16-65 years old. In addition, approximately 14% of farmers reported the existence of outsourcing service providers within the community.

■ *Difference in outsourcing decisions between smartphone users and nonusers*

Table 3 provides information regarding the difference between smartphone users and nonusers on outsourcing decisions. The results show that litchi growers who use smartphones are more likely to outsource all 11 production tasks than nonusers. Moreover, from the bottom of Table 3, we find that an average farmer in the treatment group outsourced 1.519 tasks. The figure for nonusers is 0.504. The difference between smartphone users and nonusers in the number of tasks outsourced is 1.015, which is significant at the 1% level based on the *t*-test. In addition, smartphone users outsourced more labor-intensive and technology-intensive tasks than their counterparts. On average, smartphone users outsourced 0.902 and 0.617 labor-intensive and technology-intensive tasks, respectively. The figures for nonusers are 0.287 and 0.218, respectively.

[3] Summary report of the China Internet Network Information Center: http://www.gov.cn/xinwen/2021–02/03/content_5584518.htm

Table 2. Definition and summary of treatment and covariate variables.

Variable	Definition	Mean (SD)[1]
Smartphone use	1=smartphone user, 0=otherwise	0.608 (0.488)
Gender	1=male, 0=female	0.869 (0.338)
Age	Year of household head's age	57.318 (10.405)
Education	1=elementary school, 2=middle school, 3=high school, 4=collage	2.020 (0.816)
Health	1=good, 0=normal, -1=bad	0.743 (0.498)
Training participation	1=agriculture training participant, 0=otherwise	0.643 (0.370)
Family labor	Number of 16-65 years old household members	4.116 (1.607)
Party membership	1=member of Communist Party of China, 0=otherwise	0.231 (0.422)
Cadre	1=village cadre, 0=otherwise	0.166 (0.372)
Share of litchi income	The percentage of income generated from litchi farming	42.598 (35.976)
Farm size	Size of litchi orchard (ha)	1.253 (1.157)
Income	Natural log of income per capita (10,000 Yuan[2])	0.064 (43.039)
Outsourcing service access	Perception on the easy access to outsourcing service, ranging from 1-5, 1=strongly disagree, 5=strongly agree	3.273 (1.145)
Outsourcing service provider	1=existence of agricultural production outsourcing service provider within the community, 0=otherwise	0.144 (0.351)
Huizhou	1=Huizhou farmer, 0=otherwise	0.078 (0.269)
Lianjiang	1=Lianjiang farmer, 0=otherwise	0.117 (0.322)
Maoming	1=Maoming farmer, 0=otherwise	0.230 (0.421)
Yangjian	1=Yangjian farmer, 0=otherwise	0.098 (0.298)
Qinzhou	1=Qinzhou farmer, 0=otherwise	0.193 (0.395)

[1] SD = standard deviation.

[2] 1 USD = 6.36 Yuan.

Table 3. Differences in outsourcing decisions between smartphone users and nonusers.

	Users[1]	**Nonusers**[1]	**Mean difference**[2,3]
Starter fertilizer application	0.131 (0.337)	0.023 (0.153)	0.107***
Regular fertilizer application	0.121 (0.327)	0.018 (0.133)	0.103***
Weeding	0.112 (0.315)	0.018 (0.133)	0.094***
Plant protection	0.131 (0.337)	0.015 (0.121)	0.116***
Irrigation	0.065 (0.247)	0.006 (0.077)	0.059***
Harvesting	0.342 (0.475)	0.206 (0.405)	0.136***
Pruning	0.160 (0.366)	0.060 (0.237)	0.100***
Fruit thinning	0.063 (0.244)	0.009 (0.094)	0.055***
Flower thinning	0.100 (0.300)	0.018 (0133)	0.082***
Girdling	0.108 (0.310)	0.021 (0.143)	0.087***
Grafting	0.187 (0.390)	0.110 (0.314)	0.076**
Number of tasks outsourced	1.519 (2.844)	0.504 (1.267)	1.015***
Number of labor-intensive tasks outsourced	0.902 (1.678)	0.287 (0.763)	0.615***
Number of technology-intensive tasks outsourced	0.617 (1.268)	0.218 (0.641)	0.399***
Observations	520	335	

[1] Mean and standard deviation (in parentheses).

[2] A *t*-test was applied to estimate the significance of the mean difference.

[3] ** and *** denote significance at the 5 and 1% levels, respectively.

4. Results and discussion

4.1 Covariate balance checking

Genetic matching uses a search algorithm to iteratively check and improve covariate balance. Following Sekhon and Grieve (2012) and Austin (2008), we provide information on the standardized mean difference, D-statistic, and *P*-value for the postmatching covariate balance check (Table 4). It should be noted that *P*-values are taken from *t*-tests for binary variables (i.e. gender, training participation, party membership) and from the bootstrapped Kolmogorov-Smirnov (KS) test for continuous variables (i.e. age, share of litchi income, farm size). The decrease in difference in means (standardized mean difference) and the mean discrepancies (D-statistic) may result in a higher *P*-value, which suggests an improvement in balance across the covariate distribution.

We find from Table 4 that the treatment and control groups are imbalanced before matching. Smartphone users and nonusers had different characteristics in 12 out of 18 covariates (P<0.1). Typically, smartphone users are 10 years younger than nonusers. This difference is significant at the 1% level. Moreover, smartphone users are more likely to have better health and education, access to training and outsourcing services, larger farm sizes, and party memberships. After genetic matching, the age difference decreased to 3 years and was no longer statistically significant. Significant differences persisted in only 3 out of 18 covariates. These results suggest that the covariate balance is well improved in the treatment and control groups (Frey, 2014).

To improve our understanding and for comparison purposes, we also employ PSM (one-to-one matching with replacement) to mitigate selection bias and estimate the impact of smartphone use on agricultural production outsourcing. To avoid the compression of propensity scores near zero and one, we follow Sekhon (2011) and use logistic regression to estimate the propensity score model. From Supplementary Table S1, we find that variables including age, education, party membership, cadre, share of litchi income, and farm size significantly influence farmers' decision on smartphone use. The marginal effects of these variables are -0.032, 0.037, 0.129, 0.153, 0.001, and 0.004, respectively. The finding that age has a negative impact on smartphone use is in line with that of previous studies (e.g. Kiiza and Pederson, 2012; Ma *et al.,* 2018;

Table 4. Covariate balance results.[1]

	Before matching					After matching			
	Treatment mean	**Control mean**	**SMD[2]**	**D[3]**	***P*-value[4]**	**Control mean**	**SDM**	**D**	***P*-value**
Gender	0.854	0.893	-0.110	0.039	0.093	0.867	-0.038	0.013	0.380
Age	53.098	63.868	-1.044	0.457	0.000	56.456	-0.353	0.160	0.160
Education	2.212	1.722	0.607	0.259	0.000	2.002	0.260	0.088	0.188
Health	0.815	0.629	0.422	0.168	0.000	0.815	0.000	0.004	0.971
Training participation	0.685	0.579	0.227	0.105	0.002	0.683	0.004	0.002	0.903
Family labor	4.110	4.125	-0.010	0.032	0.667	4.182	-0.048	0.071	0.254
Party membership	0.279	0.158	0.269	0.121	0.000	0.265	0.030	0.013	0.203
Cadre	0.223	0.078	0.349	0.145	0.000	0.219	0.009	0.004	0.557
Share of litchi income	44.172	40.155	0.111	0.068	0.266	44.556	-0.011	0.079	0.278
Farm size	24.383	9.872	0.272	0.173	0.000	14.867	0.178	0.088	0.088
Income	0.324	-0.340	0.518	0.206	0.000	0.072	0.196	0.096	0.209
Outsourcing service access	3.294	3.239	0.048	0.037	0.036	3.203	0.078	0.081	0.000
Outsourcing service provider	0.165	0.110	0.148	0.055	0.020	0.133	0.088	0.033	0.308
Huizhou	0.092	0.057	0.123	0.036	0.047	0.031	0.212	0.062	0.000
Lianjiang	0.121	0.110	0.033	0.011	0.632	0.123	-0.006	0.002	0.873
Maoming	0.237	0.221	0.037	0.016	0.595	0.200	0.086	0.037	0.212
Yangjian	0.087	0.116	-0.106	0.030	0.164	0.102	-0.055	0.015	0.323
Qinzhou	0.213	0.161	0.127	0.052	0.053	0.196	0.042	0.017	0.121

[1] Yulin is the reference city.

[2] SMD = standardized mean difference.

[3] The D-statistic is the maximum difference in the empirical quantile-quantile plot.

[4] *P*-values are from paired *t*-tests for binary variables and from the bootstrapped KS-test for continuous variables.

Ma and Wang, 2020; Zheng and Ma, 2021b; Zhu *et al.,* 2021a). Moreover, existing studies, such as Ma *et al.* (2018) and Deng *et al.* (2019), find that education and farm size are positively associated with farmers' decisions on smartphone and internet use. Supplementary Table S2 provides information with regard to the covariate balance results using PSM. We find that a significant difference remains in 7 out of 18 covariates. This suggests that genetic matching achieved better overall covariate balance than PSM.

4.2 Average treatment effect for the treated estimation

The ATT estimation results are presented in Table 5. From the top of the table, we find that smartphone use positively influences the number of tasks outsourced by litchi growers. The estimated ATT is 0.465 and statistically significant at the 5% level. This suggests that the average household in the treated group (i.e. smartphone users) will outsource 0.465 more tasks than it would if it did not use smartphones. Our finding is in line with Deng *et al.* (2019). Their research reveals that internet use is positively associated with farmers' decisions on outsourcing. Smartphone use facilitates agricultural production outsourcing through the potential channel of lowering transaction costs. Search and negotiation costs occur when smallholder farmers try to hire individuals and organizations for production tasks. Rural-urban migration results in rural labor shortages and rising labor costs. It is difficult to find and costly to use outsourcing services from traditional outsourcing service providers (e.g. fellow small farmers, relatives, and friends). Moreover, there is only a small number of modern outsourcing service providers (e.g. large producers, agriculture cooperatives, and agriculture service companies) who own machines and specialize in agricultural production. Combined with dispersed rural settlements and inconvenient transportation, the search costs for outsourcing services are high for litchi farmers in southern China. It is also difficult for smallholder farmers to negotiate the contract with outsourcing service providers, monitor the task outsourced, and evaluate the performance from a longterm perspective. As 98% of Chinese rural villages are covered by 4G mobile signals,[4] smartphone users can connect to the internet and communicate with outsourcing service providers in a timely and low-cost manner. Moreover, farmers can use smartphones to collect and store information (e.g. contracts, pictures, and videos) for monitoring and evaluation.

The estimated ATTs for the number of labor-intensive and technology-intensive tasks outsourced are 0.371 and 0.094, respectively. The coefficient of the former estimated ATT is statistically significant at the 5% level, and the latter is statistically significant at the 10% level. These results indicate a positive role of smartphone use on outsourcing both labor-intensive and technology-intensive tasks of litchi growers.

Additionally, we find that the treatment effect of smartphone use varies with each specific litchi production task. The estimated ATTs of smartphone use on starter fertilizer application, regular fertilizer application, weeding, plant protection, irrigation, harvesting, flower thinning, and girdling are 0.065, 0.085, 0.048, 0.069, 0.040, 0.063, 0.013, and 0.050, respectively. These coefficients are statistically significant at the 10% or higher level. Moreover, we find positive coefficients of the estimated ATTs of smartphone use on fruit thinning and pruning and negative ATTs of smartphone use on grafting. However, these coefficients are not significant. Our finding is in line with that of the existing research. In particular, Ji *et al.* (2017), Zhang *et al.* (2018), and Mi *et al.* (2020) confirm that the determinants of outsourcing decisions vary with the specific production tasks in rice, apple, and cotton farming, respectively. A possible explanation is that farm households have significant demand for certain labor-intensive outsourcing services. There are plenty of off-farm work opportunities in southern China. The use of outsourcing services can help litchi growers cope with labor shortages during the peak season and improve efficiency. For example, litchi is still harvested manually. Hiring skilled workers may help accelerate the fruit picking process without recalling household members who participate in off-farm work. Moreover, agricultural production outsourcing can assist farmers who lack production skills and machine ownership (Ji *et al.,* 2017; Zhang *et al.,* 2017). This may help explain our findings of the positive and significant effects of smartphone use on farmers' decisions regarding starter fertilizer application, regular fertilizer application, weeding, plant protection, irrigation, flower thinning, and girdling outsourcing.

[4] China daily report: http://www.chinadaily.com.cn/a/201908/02/WS5d43f3c6a310cf3e355639b3.html

Table 5. Results of average treatment effect for the treated (ATT) estimation.

	ATT (SE)[1,2]
Number of tasks outsourced	0.465** (0.285)
Number of labor-intensive tasks outsourced	0.371** (0.163)
Number of technology-intensive tasks outsourced	0.094* (0.139)
Starter fertilizer application	0.065* (0.035)
Regular fertilizer application	0.085*** (0.031)
Weeding	0.048* (0.035)
Plant protection	0.069* (0.036)
Irrigation	0.040** (0.026)
Harvesting	0.063** (0.045)
Pruning	0.021 (0.040)
Fruit thinning	0.019 (0.028)
Flower thinning	0.013* (0.034)
Girdling	0.050* (0.033)
Grafting	-0.010 (0.047)

[1] SE = robust Abadie-Imbens standard errors.

[2] *, ** and *** denote significance at the 10, 5 and 1% levels, respectively.

For comparison, we estimated the impact of smartphone use on farmers' decisions on agricultural production outsourcing using PSM, and the results are presented in Supplementary Table S3. The estimated ATT of smartphone use on the number of tasks outsourced using PSM is 0.755. Moreover, the results indicate that smartphone users will outsource 0.202 and 0.553 more labor-intensive and technology-intensive tasks, respectively. These findings confirm the positive effects of smartphone use on agricultural production outsourcing by litchi growers in southern China.

5. Conclusions

The promotion of modern ICT and agricultural production outsourcing is critical for the modernization of the Chinese small farming system. Using a sample of 855 litchi growers, this study investigates the relationship between smartphone use and farmers' decisions on agricultural production outsourcing. We employ a novel approach to control for self-selection bias for smartphone use. The genetic matching results show that smartphone use has a positive impact on agricultural production outsourcing. These results largely echo the results estimated from PSM. Moreover, we find that smartphone users tend to outsource more labor-intensive and technology-intensive tasks than nonusers. Among the 11 litchi production tasks, smartphone users were more likely to outsource tasks, including starter fertilizer application, regular fertilizer application, weeding, plant protection, irrigation, harvesting, flower thinning, and girdling, than nonusers. However, smartphone use does not significantly affect farmers' decisions on outsourcing pruning, fruit thinning, and grafting.

Our results yield several important policy implications. Agricultural production outsourcing may promote the use of machine and modern technologies in agricultural production. Since smallholders' outsourcing behavior is positively associated with smartphone use, the central and local governments should thus further improve the coverage and quality of rural mobile networks and promote the use of smartphones among farmers. Education is positively associated with farmers' decisions on smartphone use. Governments should also keep investing in rural education. Moreover, local governments should facilitate the supply of agricultural production outsourcing services in regions where there is active rural-urban migration. In particular, governments should encourage large producers, agriculture cooperatives, and agriculture service companies to provide professional outsourcing services to smallholder farmers. Governments should also cooperate with stakeholders (e.g. modern agricultural outsourcing service providers, agricultural extension workers, telecommunication companies, smartphone app developers) to disseminate agricultural outsourcing service information via smartphones. In this study, we measured agricultural production outsourcing as a binary variable, without taking into account the degree of outsourcing. It would be an interesting direction for future studies to look at the effects of smartphone use on the outsourcing degree among different agricultural production tasks.

Supplementary material

Supplementary material can be found online at https://doi.org/10.22434/IFAMR2021.0155

Table S1. Logistic regression on smartphone use.
Table S2. Covariate balance results using PSM.
Table S3. Results of ATT estimation using PSM.

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Conflict of interest

The authors declare that they have no conflict of interest.

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