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Title page

Title

The Impact of Information and Communication Technology on the Technical Efficiency of Smallholder Vegetable Farms in Shandong of China

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Competing Interests

All the authors declare none.

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Data Availability

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

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Abstract

Farmers have started to adopt Information and Communication Technology (ICT), which has considerable potential to impact farm performance. This study uses data from a 2018 survey of 763 vegetable smallholder farms in China to estimate the impact of ICT on technical efficiency (TE). We adopt propensity score matching to create a balanced sample of ICT users and non-users, and a stochastic frontier model with sample selection correction to compare the two groups' TE. After accounting for self-selection bias from both observables and unobservables, the study finds a positive effect of ICT use on TE. On average, the TE score of ICT users is 0.64, whereas ICT non-users have a lower score of 0.57. A quantile regression analysis further reveals a heterogeneous impact of ICT on TE, with the largest effects among less efficient farms. These results suggest that vegetable farmers' performance could be fostered by the widespread use of ICT.

Keywords: Information and Communication Technology (ICT), Technical efficiency, Vegetable production, Selection bias, Propensity score matching.

JEL codes: D24, Q12, Q16

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1. Introduction

China, as the foremost global producer of vegetables cultivating over half of the world's total output, has for a long time prioritized agricultural development and the increase of farm productivity (Food and Agriculture Organization, "FAO", 2023). China's agricultural production is characterized by small-scale family farms less than 2 hectares in size which account for 80% of vegetable farms (National Bureau of Statistics of China, "NBSC", 2017). One of the major challenges faced by farmers is the lack of timely and effective information for farm management (Feather and Amacher, 1994). This is especially obvious for vegetable producers in remote villages since issues such as information distortion make it difficult to ensure effectiveness and efficiency in resource use (Zheng et al., 2021). Therefore, understanding how to broaden and optimize the information channels for small farmers to improve agricultural productivity is crucial.

Since the 1990s, Information and Communication Technology (ICT), represented by all devices that allow data to be digitized, stored, and transmitted, has gradually gained popularity and profoundly changed the way farmers obtain information (Lio and Liu, 2006). The Chinese government attempted to seize this opportunity by promoting rural ICT infrastructure construction and adoption to narrow the urban-rural Digital Divide.[1] These activities, such as mobile phone trainings and the "Internet +"[2] demonstration project for farmers, have been organized and implemented with increasing intensity in rural areas since 2015. According to the 50th Statistical Report on China's Internet Development released by China Internet Network

[1] The digital divide refers to the information gap between various entities in the global digitalization process.

[2] "Internet+" refers to the integration of the Internet and other innovative information technologies into traditional industries in China.

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Information Center (2022), with the implementation of the Digital Rural Development strategy, the scale of Chinese rural netizens continues to expand. At the end of 2022, 82.2% of farm households had access to a mobile phone, and internet penetration in rural areas of China reached 58.8%. The number of rural ICT users in China amounted to 293 million or 27.9% of the national total.

The salient role of ICT in improving farmers' productivity in developing countries has been confirmed by several studies in recent years (Azhar et al., 2017; Mwalupaso et al., 2019; Zheng et al., 2021). However, previous research concentrated on arable crops such as cereals, or fruits. For example, based on a survey carried out by the Punjab Economic Research Institute in 2017, Azhar et al. (2017) illustrated the potential role of ICT in enhancing agricultural productivity by using a sample of more than 500 crop farms in India. Mwalupaso et al. (2019) reported a positive association between mobile phone use and technical efficiency (TE) for a sample of 200 corn farms in Zambia. Zheng et al. (2021) analyzed the positive impact of internet use on the TE of smallholder farms in China by using data on banana production. However, neglecting that farmers' decision to adopt ICT could be affected by various personal and demographic factors while investigating a causal link between ICT use and efficiency may lead to inaccurate results due to self-selection bias[3]. Previous studies addressed this problem by implementing propensity score matching (PSM), an instrumental variable (IV) approach, or endogenous switching regression (ESR) models (Issahaku et al., 2018; Deng et al., 2019; Twumasi et al., 2021; Zhu et al., 2021; Ma and Zheng, 2022). For example, Issahaku et al. (2018) used PSM and concluded

[3] Self-selection bias occurs when adopters differ from non-adopters due to unobserved factors that are also relevant for the outcome variable (TE in our case). Farmers who use ICT may have different characteristics, attitudes, or experiences compared to those who do not use it. This can result in a biased estimate for the effect of adoption on the outcome.

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that mobile phone use significantly improves agricultural productivity in Ghana. Zhu et al. (2021) applied stochastic frontier (SF) analysis and the ESR model to investigate how the TE of apple farmers in China is improved by internet use. Ma and Zheng (2022) used an IV approach to examine the effects of smartphone use on rural development in China.

In this study, we examine the relationship between ICT use and farm TE, based on survey data for 763 vegetable farmers in Shandong province of China. The Chinese vegetable sector is an interesting sector to investigate for at least three reasons. First, vegetables as a group are the most widely cultivated and economically essential crop in Chinese agriculture. According to FAO (2023), the vegetable planting area in China has reached 20 million hectares and vegetable output was over 600 million metric tons in 2021, accounting for 52% of the global production volume of vegetables. Considering the ever-increasing global demand, it is crucial for Chinese vegetable farmers to improve production efficiency and maximize profits, thereby meeting the growing need and maintaining its position as a leading producer and supplier of vegetables in the global market (Gale and Hu, 2012). Second, vegetable production is characterized by intensive farming with a low fallow ratio, greater use of inputs such as capital and labor, and higher yields per unit of land due to the shorter growing season and multi-harvest (Stringer et al., 2009; Silva Dias, 2010). More frequent pest and disease management as well as more careful attention to soil fertility and water management are needed during production compared to other crops (Watson et al., 2002; Dinham, 2003). Therefore, seeking out optimal production practices can help farmers grow vegetables with higher TE and guarantee their well-being. Third, ICT use might prove particularly effective in improving TE in vegetable production due to special marketing conditions. Vegetables have very limited shelf-life, and adapting vegetable production and sales timing has become increasingly critical (Ruben et al., 2007). Vegetable producers must meet

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higher requirements in terms of rapid access to market information and broadening distribution channels (Richards and Rickard, 2020). Given the increasing prominence of ICT and the urgency to improve the productivity of vegetable production, our study can shed light on whether ICT adoption affects the TE of smallholder vegetable farms in China.

The contributions of our article to the empirical literature are as follows. First, instead of using indicators similar to previous studies such as general ICT investment or ownership (Becchetti et al., 2003; Ruddock, 2006), we make use of a dataset that allows defining ICT adoption more accurately as using ICT specifically to find information for purposes of vegetable production[4]. In this way, we can make sure that farmers' ICT use is closely linked to vegetable production. Second, potential economic benefits and poverty alleviation impacts associated with vegetable production are well recognized (Schreinemachers et al., 2017), but research on vegetable production is, in general, scarce. This study contributes to closing this gap. Third, by estimating quantile treatment effects (QTE), policymakers are offered novel insights into the heterogeneous nature of the effect of ICT on TE, which can facilitate the design of tailored and effective solutions that cater to the diverse needs of different vegetable farmers subgroups.

The remainder of this paper is organized as follows: The following section briefly reviews the conceptual framework of our study. The subsequent sections describe the data collection and summary statistics as well as the empirical strategy. Section 5 shows and discusses the estimated results. The final section concludes and discusses policy implications.

[4] Farmers invest in ICT for a variety of purposes, including contacting friends and family for social networks, playing games for entertainment, messaging or calling others for problem-solving, and obtaining information online to enhance production (Lwoga, 2010; Zheng and Lu, 2021). Adopting ICT investment or ownership as a treatment variable cannot reflect the impact of ICT on farmers' production performance, which would be misleading.

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2. Conceptual Framework

In the following, we elaborate on key concepts in the productivity framework to clarify the possible pathways regarding how ICT adoption can affect the TE of farms. We start out with a simple representation of the production frontier, which represents the maximum output attainable from each input level. Productivity can be measured by the ratio of (aggregated) output over (aggregated) input (Coelli, 1995). Therefore, the farms on the frontier are technically efficient and those below are not because a greater amount of output can be achieved with the same input level or inputs can be saved without compromising the level of output. Thus, attaining elevated TE necessitates either augmenting the output with the current inputs or diminishing the inputs with the prevailing output.

ICT is a potential TE driver for several reasons: First, ICT can help farmers make better decisions and guide farmers to apply appropriate farming practices. Challenges faced by vegetable farmers in developing countries include a lack of training and skills, limited access to inputs, and inadequate agricultural extension services. ICT improves the transfer of knowledge through exchanging direct, timely, and worldwide information and ideas among farmers, experts, and other organizations to address these problems (Hobbs, 1996; Bozoğlu and Ceyhan, 2007; Aker, 2008). Also, farmers might have easier access to guidance and training from authoritative experts.

Secondly, the internet provides information on products and services and facilitates access to agricultural inputs of higher quality or lower price (Zhu et al., 2021). Farmers are no longer limited to the few options they had in the past and can keep up with factor markets by accessing the newest market information.

Third, ICT can effectively connect farmers with suppliers and customers by facilitating

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communication and thus helps rural households to distribute labor and capital in a more efficient manner (Zanello and Srinivasan, 2014; Hou et al., 2019). Timely access to market and price information enables farmers to capture market dynamics and then adjust production strategies against possible risks and losses as soon as possible (Wellman et al., 1996; Wellman et al., 2010; Galperin and Viecens, 2017).

3. Data and Descriptive Statistics

3.1 Data collection

Our empirical analysis relies on existing data from a farm-level survey that was conducted in Shouguang City during 2018 in the context of a project concerned with the influence of ICT adoption on farmers' performance. Shouguang, the "hometown" of Chinese vegetables, is located in the coastal plain area of northern central Shandong Province (Figure 1), which ranked first among the provinces in vegetable production with a total production of 82 million tons, accounting for 12% of the national vegetable supply in 2018 (NBSC, 2019). The vegetable industry in Shouguang has experienced rapid growth, which can be attributed to several factors. Firstly, the region benefits from favorable geographical conditions, including a suitable climate and fertile soil. Secondly, a mature market environment has emerged in the area, with established supply chains and distribution networks supporting the vegetable industry. Additionally, the local government has played a key role in supporting the growth of the vegetable industry through various policy measures and investment initiatives, such as stimulating R&D, organizing trade exhibitions, and supporting land transfers as well as standardization and quality management systems (Ministry of Agriculture and Rural Affairs of China, 2022). As the largest vegetable distribution center in China, Shouguang vegetables are now even exported to various countries across the globe. To take production capacity to a higher level, information technology has been gradually enhanced in Shouguang. The construction of mobile communication and wireless

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paging systems has been hastened, while the prevalence of broadband networks is on the rise. In addition, government-backed websites (e.g., http://sg.vegnet.com.cn) have been set up to release timely information on vegetable prices, wholesaling, supply, and demand, which are updated daily. Various mobile applications (e.g., Shouguang Vegetables) are also available, providing farmers with the latest news on vegetable farming and the opportunity to interact with leading experts in the field online. Therefore, exploring the effects of ICT on Shouguang vegetable producers' TE could provide policymakers to undertake further policy actions to help rural farmers benefit from ICT use in agricultural production.

Probability proportional sampling and random sampling methods were employed to select vegetable farmers in Shouguang. First, six towns were randomly chosen which include Gucheng, Hualong, Luocheng, Sunjiaji, Tianliu, and Wenjia. Second, 4 to 7 villages were randomly selected in each town. Finally, face-to-face in-depth interviews with around 15 to 25 vegetable farmers randomly selected in each of the selected villages were conducted. All the interviewers were from the research team of Northwest A & F University and have been trained for data collection purposes. A structured questionnaire was used to collect detailed information on the household head's characteristics (e.g., age, gender, and education), demographic and socioeconomic characteristics (e.g., household size, dependency ratio, and farm size), output and inputs (e.g., total income, expenditures on seeds and fertilizers) of vegetable production, and farmers' status of ICT adoption.

In total, 796 household observations were obtained. For our study, after checking for inconsistencies and excluding invalid questionnaires that had missing data, a total of 763 observations could be retained for our empirical analysis.

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3.2 Descriptive statistics and variable selection

Table 1 contains summary information on the variables used in the empirical analysis. The treatment variables *ICT use* (respondents indicating whether they use ICT to find information related to vegetable production) is used to categorize the smallholder farmers into the treatment groups of ICT users (ICT) and the control group of ICT non-users (NICT). *Output* is farmers' vegetable sales income in 2018. Input variables refer to the factors used in production. *Labor* measures the costs of household labor and hired labor (see Appendix A.1 for the details). *Land* is the total size of vegetable production (unit: mu[5]). *Fertilizer* and *Pesticide* are the expenditures on fertilizer and pesticides. Expenses for irrigation, seeds, machinery, and mulch are consolidated into *Other*.

For determinants of ICT use, previous studies pointed out household characteristics, local conditions, and geographic attributes (Issahaku et al., 2018; Mwalupaso et al., 2019; Zheng et al., 2021; Zhu et al., 2021). We choose the householder's *gender*, *age*, *education* (number of school years), *experience* (number of years working as a farmer), *certificate* (having the official professional farmer certificate), *family burden ratio* (the number of family members without own income divided by the number of members with an income), *market* (distance to closest farmers' market), *government* (distance to closest government administration), *car* (having a car), *cooperative* (participating in a cooperative), *training* (ICT training in the village), *acquaintances* (number of frequent acquaintances), *information literacy* (ability to acquire and process information, see Appendix A.2 for the definition of this variable), *social capital* (frequency and quality of social contacts, see Appendix A.3), and five locational dummy variables (*Gucheng/Hualong/Luocheng/Sunjiaji/Tianliu*) as a set of relevant covariates.

[5] 1 mu ≈ 0.0667 hectares.

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The selection of variables is grounded on theoretical economic reasoning and prior empirical findings, while the inputs and control variables undergo variance inflation factor tests to ensure they do not suffer from multicollinearity issues (see Appendices B) (Abate et al., 2014; Aldosari et al., 2019; Key and Mcbride, 2014; Smith et al., 2004). Table 1 also presents the mean and standard deviation of pooled treatment (ICT) and control (NICT) groups. There are 369 observations in the NICT group and 394 in the ICT group. Compared with the NICT group, farmers who use ICT are younger and higher educated. The ICT users are more likely to have an official professional farmer certificate and participate in the cooperative. ICT users have a higher potential to own a car. More of the farmers who live in a village with training use ICT. Farmers' information literacy and social capital positively impact their potential in using ICT. In addition, the set of variables that are significantly higher in ICT users than in non-users contains family burden ratio and distance to local government. The significant differences in these variables demonstrate a potential self-selectivity problem when estimating the ICT effect.

4. Empirical Approaches

To study the effect of ICT on TE, we follow a multi-step procedure that gradually corrects potential bias due to observables and unobservables. First, we present the results of the SF model on the original (unmatched) sample, which likely suffers from selection bias. We then use PSM to form a balanced sample of ICT users and non-users to address bias from observed characteristics. Then, Greene's (2010) sample selection model is applied to the matched sample to correct for possible bias arising from unobserved factors. We compare the TE scores of ICT users and non-users resulting from different combinations of these correction procedures, with the most reliable results being those of the sample selection SF model on the matched sample. For brevity's sake, the robustness checks relying on different matching routines, functional forms

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for frontier estimation, and an ESR model are reported in Appendix E.

4.1 Stochastic frontier model: TE estimation

TE measures an individual's ability to maximize output from given inputs and can be estimated in different ways such as data envelopment analysis and the SF model. SF model, a parametric approach, has the advantage of smaller sensitivity to measurement errors by involving a symmetric random variable to allow for statistical noise, while a one-sided random variable is included to allow for inefficiency (Bauer, 1990; Battese, 1992; Førsund et al., 1980). The general form is as follows:

$$Y_i = f(X_i; \beta) * \exp(\boldsymbol{V}_i - \boldsymbol{U}_i) \#(1)$$

where β is a vector of parameters to be estimated. Y_i is the output of the ith individual. The set of X_i is the independent input variable. $V_i \sim iid(0, \sigma_v^2)$ represents omitted variables, functional form errors, and measurement errors, and $U_i \sim iid(0, \sigma_u^2)$ denotes a non-negative random variable capturing the inefficiency effect.

A Translog (transcendental logarithmic) SF model[6], as a flexible functional form with the ability to more accurately model production processes, is used in our research to approximate the production technology as follows:

[6] The initial application of SF was based on Cobb-Douglas (CD) production function which has the restrictive properties of assuming constant output elasticities and elasticities of input substitution equal to unity (Wilson et al., 1998). However, when determining the form of a farmer's agricultural production function, the substitution elasticities between various inputs are not known in advance. However, the Translog production function does not entail as many restrictions as in the CD form, and allows for more complex relationships among the inputs (Addai et al., 2014). Additionally, we conducted a likelihood ratio test to compare the performance of the Translog SF model and the CD form and the statistic for testing H0 (CD form) against H1 (Translog form) is 53.54, indicating that the Translog SF model provides a better fit for our analysis.

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$$lnY_i = \beta_0 + \sum_{j=1}^{J} \beta_j \, lnX_{ij} + \frac{1}{2}\sum\nolimits_{j=1}^{J} \sum\nolimits_{m=1}^{M} \beta_{jm} ln(X_{ij}) ln(X_{im}) + v_i - u_i \#(2)$$

TE is defined as the ratio of observed output to the corresponding stochastic frontier output (Battese, 1992; Jondrow et al., 1982) and can be calculated as:

$$TE_i = \frac{Y_i}{f(X_i; \boldsymbol{\beta}) * \exp(\boldsymbol{V}_i)} = \exp(-\boldsymbol{U}_i) \#(3)$$

4.2 Propensity score matching: observed bias correction

This study aims to measure the average impact of ICT on small farm households' TE. Merely comparing the gaps between TE scores of users and non-users in a direct and simple way, without considering the differences in the initial conditions of the two groups of farmers, may not reflect the effect of ICT. In 1974, Rubin proposed a counterfactual framework named the Rubin Causal Model (Rubin, 1974). The counterfactual is the potential result or state of affairs that will occur if the cause does not exist (Shadish et al., 2002). Our concern is how the farmers' TE would have been impacted if those who did not use ICT had utilized it. However, as this scenario was never observed, PSM proposed by (Rosenbaum and Rubin, 1983a) is applied to create a control group with similar observed characteristics as the treatment group, thereby creating a counterfactual outcome. According to the Rubin Causal Model, this study divides sample households into a treatment group (ICT) and a control group (NICT). We use i to indicate the individual farmer and D_i to indicate whether farmer i adopts ICT or not.

For the next step, a probit regression is used to estimate farmers' propensity scores (P-score), which is defined as the conditional probability $p(z_i)$ that an individual is predicted to adopt ICT given observed characteristics z_i. The covariates that we selected for matching ICT users and non-users include the householder's gender, age, education, experience, certificate,

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distance to market, distance to government, family burden ratio, cooperative participation, training, acquaintances, information literacy, social capital, and locational variables. The propensity score is thus estimated as follows:

$$p(\mathrm{z}_i) \equiv p(D_i = 1|\mathrm{z} = \mathrm{z}_i)\#(4)$$

Then, based on the calculated P-score, each ICT user is matched with a similar non-user. Various matching algorithms are tested to evaluate the matching quality in terms of how much selection bias is reduced. In this study, we test the performance of nearest neighbor matching, radius matching, and kernel matching, and find that all three alternative methods lead to very similar results for the estimated bias. Considering the trade-off between sample size and matching quality, the best result is obtained using Gaussian kernel matching.

After matching, the standardized bias (S) is used to check if the distribution of the relevant variables is balanced in both the control and treatment groups. After conditioning the propensity score, there should be no big differences between the covariates. The expression for S is:

$$S = \frac{|\bar{z}_{\mathrm{ICT}} - \bar{z}_{\mathrm{NICT}}|}{\sqrt{\frac{s_{z,\ \mathrm{ICT}}^2 - s_{z,\ \mathrm{NICT}}^2}{2}}}\#(5)$$

where $\bar{z}_{\mathrm{ICT}}$, $\bar{z}_{\mathrm{NICT}}$, $\mathrm{s}_{z,ICT}^2$ and $\mathrm{s}_{z,NICT}^2$ represent the mean and variance of the covariate of both two groups respectively. Generally, the standardized bias should not exceed 10% (Rosenbaum and Rubin, 1983b).

4.3 Selection-corrected SF model: unobserved bias correction

PSM can eliminate the self-selection bias based on the unconfoundedness assumption, which states a strong identifying assumption that all variables influencing the adoption decision and outcome variables should be included. The standard regression techniques result in biased

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inconsistent estimators if the correlation between the unobservable factors affecting outcome and those affecting the selection process has not been considered (Greene, 2010; Lai, 2015; Bravo-Ureta et al., 2021; Vrachioli et al., 2021). Thus, the selection-corrected SF model is applied to eliminate selection bias from unobservable factors. The setting of the SF model with sample selection consists of two equations.

Sample selection:

$$D_i = h_i\gamma + e_i, with\ D_i = \begin{cases} 1, & if\ D_i > 0 \\ 0, & otherwise \end{cases} \#(6)$$

SF model:

$$Y_i = \begin{cases} f(X_i;\beta^1) * exp(\boldsymbol{v}_{1i} - \boldsymbol{u}_{1i}),\ if\ D_i = 1 \\ f(X_i;\beta^2) * exp(\boldsymbol{v}_{2i} - \boldsymbol{u}_{2i}),\ if\ D_i = 0 \end{cases} \#(7)$$

where h_i represents a vector of the individual factors which may affect farmers' choice of using ICT to obtain vegetable production information, γ is the corresponding coefficient vector, and e_i is the normalized error. Given the sample selection, the output Y_i is observed in two possible group production technologies, corresponding to the vectors of β^1 and β^2 to be estimated. $\boldsymbol{v}_{1i}$, $\boldsymbol{u}_{1i}$, $\boldsymbol{v}_{2i}$, and $\boldsymbol{u}_{2i}$ follow the same definition as in equation (1).

To derive the likelihood function of equations (6) and (7), the three symmetric errors are imposed to be independent of the vectors of explanatory variables, and assumed to be a sequence of i.i.d. bivariate normal random vectors such that

$$\begin{pmatrix} e_i \\ v_{1i} \\ v_{2i} \end{pmatrix} \sim \left(\begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho_1\sigma_{v1} & \rho_2\sigma_{v2} \\ \rho_1\sigma_{v1} & \sigma_{v1}^2 & \rho_{12}\sigma_{v1}\sigma_{v2} \\ \rho_2\sigma_{v2} & \rho_{12}\sigma_{v1}\sigma_{v2} & \sigma_{v2}^2 \end{pmatrix} \right) \quad (8)$$

where ρ_{12} denotes the correlation coefficient between V_{1i} and V_{2i}; ρ_1 denotes the correlation

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coefficient between V_{1i} and e_i; ρ_2 denotes the correlation coefficient between V_{2i} and e_i.

We use a two-step approach to estimate the equation system (Greene, 2010; Lai, 2015). In the first step, we estimate the selection equation given in (6) by the probit model. Let ρ_1 and ρ_2 be the first step, maximum likelihood estimator. Then, we estimate the frontier model (7) with the given ρ_1 and ρ_2 for the sample selection model. If ρ_1 or ρ_2 is nonzero, then the unobserved factor v_{1i} or v_{2i} affecting the y_i is correlated with the unobserved factor e_i affecting the selection process. Otherwise, the endogenous self-selection bias from unobservable factors could be ignored.

5. Results and Discussions

5.1 Results of the stochastic frontier analysis: Unmatched sample

The estimated results of the conventional SF model and selection-corrected SF model for ICT users and non-users using the whole sample are shown in Table 2. ρ_1 is statistically significant at the 1% level, which suggests the SF model with correcting selection should be considered. The likelihood ratio (LR) tests[7] in both regimes also reject the conventional SF model.

Before estimation, all variables are divided by their geometric mean, so the first-order coefficients can be interpreted as output elasticities evaluated at the sample mean (Orea, 2002; Alvarez and Arias, 2004). For ICT users, the output elasticity with respect to fertilizer is 0.30, which indicates that a 1% increase in fertilizer use will lead to a 0.3% increase in output. Land contributes the most to farm production with an output elasticity of 0.49 for farmers using ICT. The finding aligns with Bozoğlu and Ceyhan (2007)'s survey of vegetable farms in Turkey as well as Dong et al. (2019)'s research on a household-level survey of greenhouse-grown vegetable

[7] H_0: ρ_1=0. The LR statistic is (-2)*[(-316.95)-(-512.46)] =391.02 ~ $\chi^2(1)$
H_0: ρ_2=0. The LR statistic is (-2)*[(-312.30)-(-517.95)] =411.3 ~ $\chi^2(1)$

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planting in northern China. The impact of other intermediate inputs and labor on output is lower, at 0.20 and 0.08, respectively. Additional pesticide use is not found to improve ICT users' output, which is in agreement with the results of previous studies on vegetable production by Padmajani et al. (2014) in Sri Lanka and Yang et al. (2019) in China. One possible explanation is that farmers' excessive use of pesticides to mitigate the risk of crop loss caused by pests and diseases can lead to lower yields in vegetable production. In the case of ICT non-users, land size has the highest elasticity of 0.30, while the contributions of fertilizer and other inputs to output are roughly 0.26 and 0.23, respectively. The output elasticity of pesticide and labor is comparatively lower at around 0.1%. Our estimations are similar to the studies of Dong et al. (2019) and Zheng et al. (2021). The sums of all partial production elasticities for both ICT users and non-users are around 1, indicating the constant returns to scale, which is consistent with the findings of Udoh (2005) and (Shrestha et al., 2016).

The average TE scores obtained by the conventional and selection-corrected SF model for the unmatched sample are shown in Table 6. The average TE scores in the conventional SF model are 0.62 for ICT users and 0.57 for ICT non-users. In the selection-corrected SF model, slightly higher TE scores are estimated. If we control for the unobservable bias, the TE score of ICT non-users increases by 0.03 while the TE score of ICT users increases by 0.01. The TE scores obtained from two-group frontiers in the selection-corrected SF present the positive effect of ICT use on vegetable farmers' TE when considering unobserved bias.

5.2 Results of propensity score matching

We apply PSM to match ICT users and non-users to address observed bias. After estimating the P-scores and matching ICT users and non-users, there are 739 observations left. As shown in Appendix C, the standardized biases of the covariables are significantly reduced after matching,

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and their absolute values are all reduced to less than 10%, indicating that the matching is effective.

The coefficients and marginal effects of the probit model in Table 3 show how the factors impact farmers' choice of using ICT to obtain information. Gender has a significant and positive impact on using ICT, which suggests that male farmers are more likely to apply ICT to obtain information than females. Age has a significant and negative impact on the decision to use ICT, which presents that older farmers are not inclined to use ICT. This is consistent with the view that older farmers are more likely to have poorer ICT skills. Experience increases the likelihood of using ICT for agricultural information because experienced farmers are better informed about technology adoption (Okello et al., 2012; Paustian and Theuvsen, 2017). Households who live closer to the government or have ICT training in the village are more inclined to use ICT because they are often more susceptible to favorable policies designed to strengthen agriculture and benefit farmers, particularly in terms of innovative technologies (Kiiza and Pederson, 2012). Farmers who participate in agricultural cooperatives are more likely to use ICT because agricultural cooperatives often promote ICT adoption and transmit information via ICT (Abdul-Rahaman and Abdulai, 2018). Having a higher information literacy score plays a vital role in ICT adoption and its benefit from the resources available, which is in line with the previous literature (Aker, 2011; Zanello and Maassen, 2014). It should be noted that both owning a certificate and cooperative membership have the potential to affect TE, which may bias the results. We address this endogeneity issue by using the two-stage control function model suggested by Wooldridge (2015), with further elaboration and the first-stage estimates provided in Appendix D. Table 3 presents the coefficients of the generalized residuals predicted from the first stage of the control function for the variables of *certificate* and *cooperative*. The results indicate that the coefficients

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of both residuals are statistically significant, suggesting that *certificate* and *cooperative* are endogenous in the ICT decision model.

5.3 Results of the stochastic frontier analysis: Matched sample

Table 4 shows the parameter estimation results of the conventional and selection-corrected SF models for the matched sample. Compared to the unmatched sample, the output elasticities and the return to scale in both models do not change much. The estimation of the selection-corrected SF models reveals that the coefficient of the sample-selection-bias variable ρ_1 is statistically different from zero for the ICT group, which is consistent with the unmatched sample. This result again suggests the presence of selection bias when estimating the conventional SF for ICT users. Moreover, we cannot find evidence strongly supporting the significant statistic of ρ_2 which implies the selection bias in the SF of ICT non-users.

As shown in Table 5, after matching, the average TE scores of ICT users are 0.63 in conventional SF and 0.64 in selection-corrected SF, respectively, while the scores of ICT non-users are 0.57 in both conventional SF and selection-corrected SF. Our analysis shows that the difference in mean TE between ICT users and non-users is higher in the matched sample than in the unmatched sample, with an increase from 0.03 to 0.07. This indicates that neglecting selection bias resulting from both observed and unobserved factors can lead to an underestimation of the mean TE difference between ICT users and non-users. This finding aligns with previous studies by Zheng et al. (2021) and Zhu et al. (2021).

In terms of the mean score of TE, there are a few noteworthy points to consider. Firstly, our findings align with previous studies conducted by Liang et al. (2019) and Dong et al. (2019) in China, with an average score of around 0.62. However, when compared to neighboring countries that are major vegetable producers worldwide, such as Vietnam where farmers have an average

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efficiency score of 0.75 (Nguyen et al., 2021), or India where the score is 0.77 (Murthy et al., 2009), Chinese vegetable farmers appear to have lower TE scores. One possible explanation for this gap could be the land tenure system in China, which may not be as supportive of efficient vegetable farming practices as in other countries. Land use or transfer restrictions limit producers' ability to invest in land resources and improve their TE (Krusekopf, 2002). Moreover, as the largest producer and consumer of vegetables globally, China faces significant environmental challenges, such as soil pollution and water scarcity (Khan et al., 2009). These challenges make it difficult for vegetable farmers to operate efficiently, thereby lowering their TE.

Secondly, vegetable farmers tend to have lower efficiency scores than other crop farmers in China. For instance, the TE scores for apple farms and rice farming were found to be 0.83 and 0.9, respectively (Ma et al., 2018; Wang et al., 2020). The labor-intensive nature of vegetable farming work is one of the reasons for this discrepancy, as it involves tasks like hand-weeding, multi-harvesting, and diverse pest control (Stringer et al., 2009; Silva Dias, 2010). Moreover, vegetables are more susceptible to environmental factors such as changes in temperature, water availability, and soil quality than some other crops (Tripathi et al., 2016). Additionally, the lack of institutional and socio-economic support, such as extension services and cooperative assistance, can hinder the improvement of farmers' TE in China (Zheng et al., 2021). These findings suggest that the effects of efficiency might be country- or crop-specific and thus need further empirical evidence. It is also worth noting that different productivity analysis models and variable settings can influence the level of the efficiency score (Madau, 2015).

5.4 Quantile treatment effect of ICT use on TE

To design appropriate agricultural development policies, it is important to understand the

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heterogeneity of the effect of ICT on TE. To achieve this, we utilize the residualized quantile regression (RQR) model proposed by Borgen et al. (2021), which offers a flexible approach for estimating the treatment effects across the distribution of outcomes. The RQR model is estimated through a two-step approach in our study. First, the treatment variable (ICT) is regressed on control variables using ordinary least squares, which allows us to decompose the variance of the treatment variable into two components: a portion that can be explained by the observed control variables and a residual component that is orthogonal to the controls. In the second step, the outcome variable (TE) is regressed on the residualized treatment variable using the method of minimum absolute deviation. At last, QTE can be computed from observed data while adjusting for selection bias by comparing quantiles (τ) of the outcome distribution for individuals with different treatment values as $QTE^{\tau} = Q_{ICT}^{\tau} - Q_{NICT}^{\tau}$.

The results can be found in Table 6. The coefficients except for the quantile at 90th exhibit a positive and significant relationship between ICT use and TE, which is in line with our previous results. Specifically, from the 10th to 25th percentile, the coefficient for the ICT treatment has a slight increase. The largest effect is observed at the 25th percentile, with a coefficient of 0.12, suggesting that the ICT treatment has a more pronounced effect on the lower quantiles of the distribution (Zheng et al., 2021). These findings suggest that adopting ICT is likely to be more effective for less efficient farms to begin with, as they have more room for improvement. The effect is not significantly different from zero at the 90th percentile, indicating that ICT use is less effective for the most efficient farms, potentially because they have already optimized their production processes to a greater extent with the help of other information channels.

6. Conclusion and Policy Implication

This study uses data from a survey of 763 small vegetable farms in China to estimate the impact

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of farmers' ICT use on vegetable production performance. Propensity score matching and selection-corrected stochastic frontier model are combined to correct for selection bias from both observed and unobserved factors. The results reveal that the difference in TE between ICT users and non-users is statistically and economically significant after addressing both observed and unobserved biases, which highlights the potential benefits brought by ICT use to vegetable production in China. Further empirical analysis conducted by the quantile treatment effect model reveals that the impact of ICT on TE is heterogeneous, with the largest effects observed among the less efficient farms, and decreasing as we move towards the median and becoming statistically insignificant for the most efficient farms.

The findings have several important policy implications: First, our findings indicate the considerable potential of ICT use to improve TE in the sector, which suggests increasing government subsidies to improve the penetration rate of ICT and further promote the modernization of rural areas, especially the investment in broadband infrastructure. Second, ICT use appears to be particularly effective for low-TE farms, indicating that those farms should be targeted with greater focus. Third, results from the propensity score model suggest that effective ways to foster ICT adoption are the provision of training and enhancing information literacy in general. Farmers might still lack the ability to make effective use of information acquired by ICT, which can be found in our survey that only 16% of farmers have ICT training in their villages. Thus, the government should encourage and guide farmers to use ICT to obtain agricultural information by providing ICT-related training, stimulate the provision of agricultural information by, e.g., extension services, and cultivate their information awareness and literacy. Especially for the less technical efficient and less-educated farmers, their level of using the ICT should be improved so that they can access and apply fundamental information and benefit from

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it. Fourth, as a more ancillary result, the department of agricultural information services should provide effective guidance and regulation which will lead to an optimum match between information supply and demand thereby facilitating farmers' utilization of information resources via ICT.

Limitations and outlook of our study include the fact that our survey sample is limited to a cross-sectional data set. Panel data that might be obtained in future research will allow more rigorous treatment of endogeneity due to time-invariant unobservables and additionally better reflect the impact of ICT on productivity change. As a future outlook, new ICT developments might bring about new implications for farm performance. The Central Government of China proposed to accelerate the planning and construction of the fifth-generation communication technology (5G) in rural areas, establish the agricultural big data system, and promote the in-depth integration of new-generation information technology with agricultural production and operation. Therefore, the advent of the 5G era is not only a new opportunity for agricultural development but also a new chapter to study new ICT developments' implications for farm performance.

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Figures

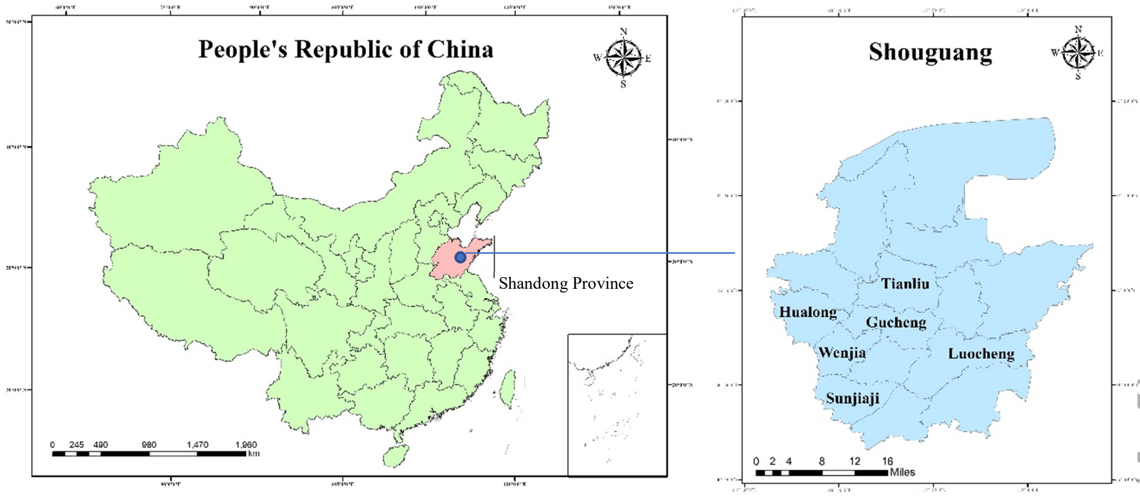

Figure 1 Map of the study area.

Source: Use ArcGIS Map to draw.

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Table 1 Variable Selection and Descriptive Statistics.

Variable	Interpretation	Mean			
		All	ICT	NICT	Diff.
Treatment Variable:					
ICT	Does farmer use ICT to obtain vegetable production information?		0.52	0.48	
			(0.50)	(0.50)	
Outcome Variable:					
Output	Vegetable sales revenue in 2018 (10,000 yuan)	13.23	15.07	11.25	3.82***
		(-12.71)	(-14.55)	(-10.04)	
		4.06	*4.25*	*3.87*	*0.38**
		(-2.71)	*(-2.78)*	*(-2.63)*	
Input Variables:					
Labor	Household labor costs and hired labor costs (10,000 yuan; Appendix A.1)	6.16	6.16	6.15	0.01
		(-4.39)	(-4.43)	(-4.36)	
		2.30	*2.14*	*2.47*	*-0.33***
		(-2.06)	*(-2.02)*	*(-2.10)*	
Land	The farm size of vegetables (mu)	3.97	4.32	3.61	0.71*
		(5.30)	(5.63)	(4.91)	
Fertilizer	The costs of fertilizer (10,000 yuan)	1.83	1.86	1.80	0.06
		(-1.79)	(-1.96)	(-1.60)	
		0.62	*0.60*	*0.65*	*-0.05*
		(-0.54)	*(-0.59)*	*(-0.49)*	
Pesticide	The costs of pesticide (10,000 yuan)	0.51	0.57	0.44	0.13***
		(-0.64)	(-0.72)	(-0.54)	
		0.18	*0.19*	*0.16*	*0.03**
		(-0.26)	*(-0.30)*	*(-0.21)*	
Other	The costs of irrigation, seeds, plastic and machinery (10,000 yuan)	1.15	1.27	1.03	0.24**

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		(-1.65)	(-1.90)	(-1.33)	
		0.36	*0.38*	*0.34*	*0.04*
		(-0.44)	*(-0.54)*	*(-0.29)*	
Control Variables:					
Gender	Gender of household head	0.97	0.98	0.95	0.03***
		(0.17)	(0.12)	(0.22)	
Age	Age of household head	51.85	49.17	54.71	-5.54***
		(8.68)	(8.39)	(8.07)	
Education	How many years of education does household head have?	8.24	8.63	7.83	0.80***
		(2.63)	(2.41)	(2.80)	
Experience	How many years has household head been engaged in vegetable production?	20.695	21.02	20.33	0.69
		(10.18)	(9.39)	(10.96)	
Certificate	Does household head have an official professional farmer certificate? 1 =Yes; 0=No	0.06	0.08	0.04	0.04**
		(0.24)	(0.27)	(0.20)	
Ratio	Dependency ratio of those typically not in the labor force and those typically in the labor force	0.75	0.87	0.63	0.24***
		(0.67)	(0.72)	(0.59)	
Market	The distance from household to markets (km)	1.97	2.01	1.92	0.09
		(3.23)	(3.83)	(2.44)	
Government	The distance from household to local governments(km)	6.92	8.11	5.65	2.46***
		(7.17)	(9.35)	(3.15)	
Cooperative	Does household participate in a cooperative? 1=Yes; 0=No	0.10	0.14	0.06	0.08***
		(0.30)	(0.34)	(0.23)	
Acquaintance	The number of frequent acquaintances	20.95	22.73	19.04	3.69***
		(16.19)	(16.94)	(15.14)	
Car	Does household own a private car? 1=Yes; 0=No	0.50	0.56	0.45	0.11***
		(0.50)	(0.50)	(0.50)	
Training	Is there ICT training in the village?	0.16	0.20	0.13	0.07***
		(0.37)	(0.40)	(0.33)	
Information literacy	Ability to acquire and utilize information (Appendix A.2)	53.44	55.64	51.09	4.55***

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		(6.48)	(5.89)	(6.27)	
Social capital	Frequency and quality of social contacts (Appendix A.3)	41.47	42.45	40.42	2.03***
		(6.77)	(6.98)	(6.39)	
IV: cooperative	Is there a cooperative in the village?	0.57	0.65	0.47	0.18***
		(0.50)	(0.48)	(0.50)	
IV: certificate	Share of certificate owner in the village	0.06	0.07	0.05	0.02***
		(0.06)	(0.06)	(0.06)	

Source: Farm household survey (2018).
Notes: Values in bold italics show the per mu data of farm inputs and output in vegetable production; Other values measures per farm. Standard deviation in parentheses. *, **, and *** denote mean difference (t-test) between ICT non-users (NICT) and users (ICT) at the 10%, 5%, and 1% significant levels, respectively.

Note:

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Table 2 Stochastic Production Frontiers Estimates: Unmatched Sample.

Variables	Conventional SF		Selection-corrected SF	
	ICT	NICT	ICT	NICT
Constant	0.268***	0.482***	0.352**	0.278
	(0.104)	(0.107)	(0.153)	(0.170)
Labor	0.059	0.071	0.076	0.090
	(0.048)	(0.053)	(0.054)	(0.067)
Land	0.538***	0.363***	0.488***	0.305***
	(0.054)	(0.069)	(0.071)	(0.084)
Pesticide	-0.067*	0.093**	-0.069	0.111**
	(0.035)	(0.037)	(0.043)	(0.050)
Fertilizer	0.280***	0.228***	0.296***	0.255***
	(0.047)	(0.042)	(0.061)	(0.056)
Others	0.199***	0.227***	0.199***	0.225***
	(0.050)	(0.049)	(0.059)	(0.069)
Labor*Labor	0.051	-0.086	0.070	-0.072
	(0.104)	(0.108)	(0.116)	(0.164)
Land*Land	-0.331***	-0.011	-0.318***	0.008
	(0.095)	(0.112)	(0.107)	(0.121)
Pesticide*Pesticide	-0.025*	0.024	-0.025*	0.014
	(0.013)	(0.047)	(0.013)	(0.049)
Fertilizer*Fertilizer	0.014	0.032	0.008	0.041
	(0.078)	(0.054)	(0.126)	(0.077)
Others*Others	0.099	0.057	0.099	0.063
	(0.066)	(0.050)	(0.092)	(0.084)
Labor*Land	0.079	-0.013	0.082	-0.044
	(0.073)	(0.081)	(0.078)	(0.095)
Labor* Pesticide	-0.068	-0.097**	-0.056	-0.100*
	(0.048)	(0.048)	(0.059)	(0.055)
Labor* Fertilizer	-0.051	-0.044	-0.032	0.000
	(0.065)	(0.053)	(0.076)	(0.075)
Labor* Others	0.090	0.175***	0.074	0.171**
	(0.068)	(0.059)	(0.084)	(0.070)
Land* Pesticide	-0.017	-0.085*	-0.024	-0.067
	(0.039)	(0.050)	(0.038)	(0.051)
Land* Fertilizer	0.143**	0.049	0.162*	0.034
	(0.070)	(0.072)	(0.087)	(0.088)
Land* Others	0.037	0.032	0.017	0.011
	(0.069)	(0.071)	(0.089)	(0.090)
Pesticide* Fertilizer	0.043	-0.004	0.046	-0.013
	(0.045)	(0.044)	(0.058)	(0.051)
Pesticide * Others	-0.042	0.092**	-0.044	0.085
	(0.046)	(0.046)	(0.044)	(0.058)

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Fertilizer *Others	-0.123**	-0.174***	-0.123	-0.157***
	(0.060)	(0.043)	(0.088)	(0.061)
Gucheng	0.341***	0.203	0.350***	0.278*
	(0.125)	(0.124)	(0.133)	(0.154)
Hualong	0.204*	0.073	0.242*	0.159
	(0.119)	(0.119)	(0.132)	(0.120)
Luocheng	0.352***	0.362***	0.354***	0.385***
	(0.119)	(0.124)	(0.120)	(0.143)
Sunjiaji	0.357***	0.013	0.320**	0.015
	(0.116)	(0.129)	(0.128)	(0.143)
Tianliu	0.395***	0.429***	0.374***	0.467***
	(0.120)	(0.125)	(0.133)	(0.139)
ρ			-0.475***	0.341
			(0.179)	(0.228)
σ u	0.652***	0.800***	0.616***	0.734***
	(0.113)	(0.070)	(0.126)	(0.120)
σ v	0.380***	0.325***	0.416***	0.420***
	(0.061)	(0.043)	(0.061)	(0.068)
Log-likelihood	-316.947	-312.301	-512.460	-517.948
N	394	369	394	369

Source: Farm household survey (2018).

Notes: Asterisks denote significance at the 10% (*), 5% (**), and 1% (***) levels. Numbers in the parentheses are the standard errors. The LR statistic for testing H0 (two-regime model) against H1 (one-regime model) is 42.62, so we adopt the two-regime model.

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Table 3 Probit Model Marginal Effects: Unmatched and Matched Sample.

	Unmatched		Matched	
	Coefficient	Marginal effect	Coefficient	Marginal effect
Gender	0.677**	0.201**	0.673**	0.207**
	(0.324)	(0.095)	(0.322)	(0.098)
Age	-0.051***	-0.015***	-0.051***	-0.016***
	(0.008)	(0.002)	(0.008)	(0.002)
Education	-0.005	-0.001	-0.007	-0.002
	(0.022)	(0.006)	(0.022)	(0.007)
Certificate	1.173	0.348	1.073	0.330
	(0.728)	(0.215)	(0.774)	(0.237)
Experience	0.028***	0.008***	0.028***	0.009***
	(0.006)	(0.002)	(0.007)	(0.002)
Ratio	0.109	0.032	0.112	0.034
	(0.084)	(0.025)	(0.083)	(0.026)
Government	0.051***	0.015***	0.049***	0.015***
	(0.014)	(0.004)	(0.015)	(0.004)
Market	0.013	0.004	0.012	0.004
	(0.022)	(0.006)	(0.021)	(0.007)
Training	0.339**	0.101**	0.322**	0.099**
	(0.157)	(0.046)	(0.157)	(0.048)
Cooperative	1.087**	0.323**	0.971**	0.299**
	(0.465)	(0.137)	(0.476)	(0.145)
Car	0.096	0.029	0.101	0.031
	(0.112)	(0.033)	(0.111)	(0.034)
Acquaintances	-0.002	-0.001	-0.001	-0.000
	(0.004)	(0.001)	(0.004)	(0.001)
Information literacy	0.071***	0.021***	0.071***	0.022***
	(0.010)	(0.003)	(0.010)	(0.003)
Socialcapital	0.000	0.000	0.001	0.000
	(0.008)	(0.003)	(0.009)	(0.003)
Gucheng	-0.072	-0.021	-0.098	-0.030
	(0.237)	(0.070)	(0.234)	(0.072)
Hualong	-0.072	-0.021	-0.077	-0.024
	(0.210)	(0.062)	(0.208)	(0.064)
Luocheng	-0.189	-0.056	-0.211	-0.065
	(0.226)	(0.067)	(0.226)	(0.069)
Sunjiaji	0.127	0.038	0.129	0.040
	(0.212)	(0.063)	(0.207)	(0.064)
Tianliu	0.542**	0.161**	0.466**	0.143**
	(0.233)	(0.069)	(0.228)	(0.070)
Residual_cooperative	-0.549**	-0.163**	-0.462*	-0.142*
	(0.265)	(0.078)	(0.270)	(0.083)
Residual_certificate	-0.697*	-0.207*	-0.626	-0.193
	(0.388)	(0.115)	(0.411)	(0.126)
Constant	-3.021***		-3.027***	
	(0.785)		(0.780)	
Log-likelihood	--398.515		-399.593	

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N	763	763	739	739

Source: Farm household survey (2018).
Notes: Asterisks denote significance at the 10% (*), 5% (**), and 1% (***) levels. Numbers in the parentheses are the standard errors.

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Table 4 Stochastic Production Frontiers Estimates: Matched Sample.

Variables	Conventional SF		Selection-corrected SF	
	ICT	NICT	ICT	NICT
Constant	0.227**	0.461***	0.311*	0.336**
	(0.107)	(0.106)	(0.164)	(0.156)
Labor	0.075	0.093*	0.086	0.115*
	(0.049)	(0.053)	(0.056)	(0.068)
Land	7.513***	0.371***	0.469***	0.329***
	(0.055)	(0.070)	(0.072)	(0.087)
Pesticide	-0.060*	0.107***	-0.063	0.124**
	(0.036)	(0.038)	(0.045)	(0.051)
Fertilizer	0.294***	0.224***	0.306***	0.236***
	(0.048)	(0.042)	(0.062)	(0.055)
Others	0.187***	0.202***	0.190***	0.193***
	(0.051)	(0.049)	(0.061)	(0.072)
Labor*Labor	0.080	-0.030	0.092	-0.021
	(0.106)	(0.110)	(0.118)	(0.162)
Land*Land	-0.306***	0.004	-0.301***	0.031
	(0.097)	(0.112)	(0.107)	(0.117)
Pesticide*Pesticide	-0.021*	0.052	-0.021	0.038
	(0.013)	(0.048)	(0.014)	(0.047)
Fertilizer*Fertilizer	0.003	0.052	-0.004	0.055
	(0.084)	(0.054)	(0.128)	(0.072)
Others*Others	0.089	0.093*	0.089	0.097
	(0.067)	(0.054)	(0.096)	(0.091)
Labor*Land	0.066	-0.048	0.068	-0.079
	(0.074)	(0.082)	(0.080)	(0.094)
Labor* Pesticide	-0.092*	-0.095*	-0.079	-0.087
	(0.049)	(0.050)	(0.062)	(0.055)
Labor* Fertilizer	-0.023	-0.088	-0.012	-0.065
	(0.067)	(0.054)	(0.077)	(0.070)
Labor* Others	0.112	0.253***	0.094	0.257***
	(0.069)	(0.065)	(0.084)	(0.073)
Land* Pesticide	-0.009	-0.077	-0.011	-0.064
	(0.039)	(0.050)	(0.040)	(0.054)
Land* Fertilizer	0.152**	0.060	0.168*	0.054
	(0.072)	(0.074)	(0.089)	(0.088)
Land* Others	-0.004	0.003	-0.015	-0.031
	(0.071)	(0.072)	(0.091)	(0.095)
Pesticide* Fertilizer	0.045	-0.006	0.049	-0.014
	(0.046)	(0.044)	(0.060)	(0.051)
Pesticide * Others	-0.030	0.070	-0.035	0.061
	(0.047)	(0.048)	(0.047)	(0.062)
Fertilizer *Others	-0.130**	-0.197***	-0.126	-0.178***

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	(0.061)	(0.044)	(0.091)	(0.061)
Gucheng	0.367***	0.228*	0.370***	0.280*
	(0.127)	(0.122)	(0.135)	(0.153)
Hualong	0.260**	0.099	0.290**	0.172
	(0.123)	(0.117)	(0.136)	(0.124)
Luocheng	0.368***	0.355***	0.367***	0.368***
	(0.121)	(0.121)	(0.122)	(0.142)
Sunjiaji	0.313***	-0.011	0.291**	-0.020
	(0.121)	(0.126)	(0.131)	(0.138)
Tianliu	0.410***	0.427***	0.387***	0.442***
	(0.123)	(0.122)	(0.135)	(0.137)
ρ			-0.430**	0.349
			(0.190)	(0.275)
σ u	0.618***	0.820***	0.581***	0.821***
	(0.139)	(0.066)	(0.143)	(0.093)
σ v	0.397***	0.304***	0.430***	0.359***
	(0.071)	(0.042)	(0.064)	(0.066)
Log-likelihood	-303.130	-303.363	-499.624	-506.804
N	377	362	377	362

Source: Farm household survey (2018).

Notes: Asterisks denote significance at the 10% (*), 5% (**), and 1% (***) levels. Numbers in the parentheses are the standard errors.

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Table 5 Technical Efficiency: Unmatched and Matched Sample.

	NICT	ICT	Diff.
Unmatched			
Conventional SF	0.575	0.616	0.042***
	(0.178)	(0.155)	
Selection-corrected SF	0.597	0.631	0.033***
	(0.150)	(0.145)	
ESR	0.590	0.648	0.058***
	(0.182)	(0.143)	
Matched			
Conventional SF	0.572	0.629	0.058***
	(0.182)	(0.144)	
Selection-corrected SF	0.573	0.643	0.070***
	(0.174)	(0.135)	
ESR	0.585	0.658	0.073***
	(0.188)	(0.135)	

Source: Farm household survey (2018).

Notes: Asterisks denote mean differences (t-test) between ICT non-users and ICT users are significant at the 10% (*), 5% (**), and 1% (***) levels. The numbers in the parentheses are the standard deviations.

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Table 6 Quantile treatment effects of ICT on TE.

Quantile level	Coef.	Std. Err
10th	0.096***	0.028
25th	0.115***	0.026
50th	0.079***	0.018
75th	0.044***	0.010
90th	0.001	0.010

Source: Farm household survey (2018).

Notes: Asterisks denote significance at the 10% (*), 5% (**), and 1% (***) levels. Standard errors are based on 1000 bootstrap repetitions in both the first-step residualization and the second-step QTE estimation.

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