Impacts of marketing contracts on technical efficiency of citrus production

Farmers seeking marketing contracts for product sales need to adjust their production behaviour in advance to meet the product attributes required by market buyers. However, little is known about whether marketing contract users are more efficient in farm production than non-users. This study contributes to the literature by examining the impacts of marketing contracts (written contracts, verbal contracts, and no contracts) on technical efficiency, taking citrus production in Jiangxi Province, China, as an example. We first use a stochastic production frontier (SPF) model to calculate the technical efficiency scores of citrus production at the individual level. Then, we use a multinomial endogenous switching regression (MESR) model, which mitigates selection bias issues arising from observed and unobserved factors, to estimate the treatment effects of marketing contract choices on technical efficiency. The SPF model estimates show that the mean technical efficient score of citrus production is 0.626, ranging between 0.021 and 0.892. The MESR model estimates reveal that the average technical efficiency scores for written and verbal contract users are 14% and 2% higher than those for no-contract users. The average technical efficiency score for written contract users is 8% higher than for verbal contract users. Our findings highlight the importance of helping citrus farmers use marketing contracts, especially formal written contracts when selling their products, which can help increase technical efficiency and farm productivity.

Keywords: Marketing contracts; Technical efficiency; Citrus production; Stochastic production frontier; Multinomial endogenous switching regression

JEL code: C21; D61; L14; Q13

1 Introduction

The stable connection between smallholder farmers and markets is essential to reducing risks and uncertainties of product sales and increasing rural incomes. However, in many developing countries, smallholder farmers face various barriers (e.g., inadequate information on output markets, high transaction costs, and market failure) when entering into domestic and international markets (Dey and Singh, 2023; Mishra et al., 2019; Miyata et al., 2009; Otsuka et al., 2016). These barriers prevent farmers from benefiting from agricultural marketing and challenge the achievements of the United Nations' sustainable development goals. Therefore, linking farmers to markets becomes essential to improving farm economic performance and boosting sustainable rural development.

A marketing contract is an institutional arrangement that helps better connect farmers to markets. Marketing contracts allow buyers and sellers to pre-agree on terms such as the price, quantity, timing, quality standards, and technical requirements for the products (Bellemare and Lim, 2018). Therefore, marketing contracts enable to decrease transaction costs, stabilise marketing channels, reduce uncertainties associated with sales prices, and mitigate market failures (Bellemare and Lim, 2018; Dsouza et al., 2023; Ruml et al., 2022; Williamson, 2019).

The importance of marketing contracts in improving farm performance and facilitating rural development has been well documented. Several studies have shown that marketing contracts affect the adoption of sustainable farm practices (Dubbert et al., 2023; Ricome et al., 2016), crop output (Abdoulaye and Fambaye, 2020), farm income (Khan et al., 2019), multidimensional poverty (Ogutu et al., 2020), dietary diversity (Ochieng and Ogutu, 2022), and food security (Soullier and Moustier, 2018). For example, Abdoulaye and Fambaye (2020) showed that marketing contracts boosted rice production and income of farmers in Senegal. Ruml et al. (2022) found that production with marketing contracts led to a 33% increase in palm oil farmers' income in Ghana because marketing contracts increased planting specialisation and sales volumes.

Moreover, the usage of marketing contracts may also affect the production efficiency. Buyers who prefer marketing contracts for transactions have specific requirements for the products delivered by farmers, such as quality, quantity, colour, shape and sugar content. In response, farmers who prefer to sell their products with marketing contracts would have to adjust their production behaviour in advance to better align with buyers' requirements on product attributes. The fact suggests that marketing contract users and non-users may have different production behaviours when using production inputs (e.g., fertilisers, pesticides, and labour), leading to differences in production efficiency. Nevertheless, no previous studies have explored the associations between marketing contract choices and the production efficiency of crop production.

This study adds to the literature by investigating the impact of marketing contract choices on technical efficiency, using citrus production in Jiangxi province as an example. Jiangxi province is one of China's eight major citrus-producing regions,[1] growing around 336.2 thousand hectares of citrus and producing 4.45 million tonnes in 2021 (NBSC, 2022). However, the citrus output per unit area in Jiangxi province is lower than the national average in the last decade, and the growth rate is lower than in other provinces (Figure 1). For example, in 2021, Jiangxi's citrus yield per unit area was only 13.22 tonnes per hectare (CRSY, 2022). In comparison, the citrus yield per unit area was 26.20 tonnes per hectare in Guangxi, 27.59 tonnes per hectare in Fujian, and 19.15 tonnes per hectare at the national average. Therefore, increasing citrus productivity in Jiangxi Province is essential for improving national citrus output and boosting rural development.

[Insert Figure 1 here]

Productivity can be improved by increasing the levels of production inputs and

[1] The eight citrus planting areas of China include Fujian, Guangdong, Guangxi, Hubei, Hunan, Jiangxi, Zhejiang, and Chongqing (MARA, 2008).

improving technical efficiency (Ma et al., 2019; Raphael, 2008; Ubabukoh and Imai, 2023). Technical efficiency refers to the ability to increase outputs with defined inputs or reduce inputs with defined outputs, which considers both inputs and outputs and fully reflects the "optimal" relationship between inputs and outputs (Selorm et al., 2023; Zheng et al., 2021). Due to resource and budget constraints, increasing farm productivity by increasing production inputs is not conducive to sustainable agricultural production, as this strategy also increases production costs. In comparison, improving technical efficiency is an optimal strategy to increase farm productivity because it only considers reallocating existing resources for efficient management without adding extra production costs (Dagar et al., 2021; Ma et al., 2023a).

This study makes two contributions to the literature. First, we consider three types of marketing contracts, including written, verbal, and no contracts, and compare their pairwise differences in technical efficiency. Written contracts facilitate transactions through clear terms, obligations, and penalties and regulate behaviour by law (Poppo and Zenger, 2002). Verbal contracts facilitate transactions and optimise social relationships through relational governance, and they are an important transaction form that promotes trust between farmers and buyers (Malcomson, 2012; Yulianti et al., 2020). Because using written and verbal contracts leads to different risk diversification and benefit distribution effects (Abebe et al., 2013; Barrett et al., 2012), farmers who prefer written contracts and verbal contracts may behave differently in citrus production. Thus, it is interesting to see whether there is a difference in the technical efficiency of citrus production between written and verbal contract users. The findings could provide insights regarding whether written or verbal contracts should be promoted among smallholder farmers. Second, we employ the stochastic production frontier model to calculate the technical efficiency of citrus production. Then, we use the multinomial endogenous switching regression (MESR) model to estimate the pairwise treatment effects of marketing contract choices. In particular, the MESR model allows the treatment effect variable to have more than two choices and mitigates the selection bias issues of marketing contract choices arising from observable and unobservable factors (Pan et al., 2021; Setsoafia et al., 2022).

This paper is structured as follows. Section 2 introduces the background of citrus production and marketing contracts. Section 3 presents the estimation strategies. Section 4 introduces data and descriptive statistics. Section 5 presents the results and discussion. Section 6 concludes the paper and provides policy implications.

2 Background

Citrus is one of the most popular fruits in the world. In 2021, the total global output of citrus was 162 million tonnes (FAOSTAT, 2022). China is the largest citrus-producing country regarding country-level total output and planting areas. In 2021, China produced citrus of 46.67 million tonnes, accounting for 28.85% of the global total output (FAOSTAT, 2022). The citrus-growing area was 3.03 million hectares, contributing to 29.66% of global total growing areas. Brazil, the second-largest citrus producer, grew 18.88 million tonnes of citrus and produced 0.7 million tonnes in the same year. Despite the significant growing regions and output of citrus in China, the citrus yield per unit of land was very low, with only 15.39 tonnes per hectare in 2021 (FAOSTAT, 2022). Citrus yield in China is much lower than that in other major citrus-producing countries such as Brazil (27.11 tonnes per hectare), Turkey (32.22 tonnes per hectare), and Iran (28.11 tonnes per hectare) and even below the world average (15.83 tonnes per hectare) (FAOSTAT, 2022). Therefore, there is a great need to increase citrus yield.

In China, Citrus farmers traditionally sell their products at the spot markets. Because citrus is not a storage-resistant fruit, the freshness of citrus plays an essential role in determining its price and market demand. Due to price fluctuations and market uncertainties, citrus farmers may have to store their products if they cannot sell them timely at the spot markets (Naseer et al., 2019). Moreover, citrus is mainly produced in mountainous or hilly areas, where markets are not well developed and not easily accessible, making it difficult for farmers to sell by themselves at the spot markets. Therefore, intermediaries become price controllers, and farmers bear high transaction costs, which makes it challenging to get the expected profit (Siddique et al., 2018).

The emergence and usage of marketing contracts can tackle the problems facing citrus farmers. Citrus farmers use three types of marketing contracts when selling their products to the markets: written contracts, verbal contracts, and no contracts (i.e. spot market sales). Written and verbal contracts refer to a case in which buyers and sellers agree on the transaction terms such as price, quantity, time, and product quality, and the seller promises to deliver, and the buyer promises to buy. Moreover, written contracts require both parties to sign the contract, which is legally binding. Thus, penalties may exist for breaking the contracts (Minot and Sawyer, 2016; Poppo and Zenger, 2002). In comparison, verbal contracts are informal agreements. The parties agree on the terms only verbally, which is not legally binding. Trust and reputation are the main enforcement methods of verbal contracts (Wolf et al., 2001; Yulianti et al., 2020). Finally, no contracts refer to spot market transactions. Buyers and sellers meet in the trading markets, agree on the price based on supply and demand without prior commitment, and instantly complete payment and delivery of goods.

As emphasised earlier, buyers who use written and verbal contracts usually have requirements on agreed product attributes such as quality, quantity, colour, and size of the delivered products. In response, farmers who intend to use marketing contracts to sell their products must adjust their production behaviour (e.g., citrus orchard management technologies) to better align with the buyers' requirements. Therefore, this study adds new insights to the literature by exploring the relationship between marketing contracts and the technical efficiency of citrus production.

3 Estimation strategies

3.1 Stochastic production frontier model

Technical efficiency is usually calculated by either the data envelopment analysis (DEA) model (Cloutier and Rowley, 1993; Nodin et al., 2022; Stokes et al., 2007) or the stochastic production frontier (SPF) model (Alvarez et al., 2008; Latruffe et al., 2017; Ma et al., 2023a). The DEA is a non-parametric model that attributes production frontier changes to inefficiencies and assumes the absence of stochastic errors. The DEA model requires data accuracy. However, obtaining accurate agricultural data is difficult because of unpredictable natural disasters and weather changes. Compared to the DEA model, the SPF model is a parametric model, which helps distinguish the inefficiency term from stochastic variation and makes reasonable error distribution assumptions. Therefore, the SPF model is more appropriate for analysing data collected from agricultural sectors. Because we analyse data collected from citrus farmers, we apply the SPF model in this study.

Following previous studies (Bezat, 2011; Lampach et al., 2021), the production function with the SPF model framework is specified as follows:

$$Y_i = f\,(K_i) + \varepsilon_i, with\, \varepsilon_i = v_i - u_i \tag{1}$$

where Y_i denotes the citrus yield of farmer i; K_i is a vector of input factors (e.g., fertiliser, pesticide, and labour); and ε_i is the error term, which consists of random noise v_i and an inefficiency term u_i.

3.2 Selection of an appropriate functional form

The production function, i.e. Equation (1), can be estimated by two alternative functional forms: the Cobb-Douglas production function and the Translog function. The parameters estimated by the Cobb-Douglas function are equal to the elasticity coefficients of the variables (Koopman and Wacker, 2023; Latruffe et al., 2017), which directly reflect the corresponding economic implications. The Translog function incorporates the effects of the interactions between the input variables, which overcomes the disadvantage of the Cobb-Douglas function, where the elasticity of substitution is fixed at one (Biagini et al., 2022; Lin et al., 2022).

We use three steps to select the most appropriate functional form. First, we use the Cobb-Douglas function to estimate three production functions by assuming that the error term in Equation (1) has half-normal, truncated, and exponential distributions, respectively (see Table A1 in the Appendix). The likelihood ratio tests reveal that the Cobb-Douglas production form with exponential distribution should be considered. Second, we use the Translog functional form to estimate three production functions by assuming that the error term in Equation (1) has half-normal, truncated, and exponential distributions, respectively (see results in Table A2 in the Appendix). The likelihood ratio tests reveal that the Translog functional form with an exponential distribution should be considered. Third, using the likelihood ratio test, we further compare the two functional forms identified from the first two steps. The results show that the Cobb-Douglas production form with exponential distribution is nested in the Translog functional form with exponential distribution (p-value=0.001). The finding suggests that the Translog functional form with an exponential distribution in error term is preferred.

The Translog functional form used for estimating the production function, i.e. Equation (1), is specified as follows:

$$\begin{aligned} ln\,(Y_i) = \alpha_0 + \sum_{j=1}^{4} \alpha_j\, ln\,(K_{ij}) + 0.5 \sum_{j=1}^{4} \alpha_{jj}\, ln\,(K_{ij})^2 \\ + \sum_{j=1}^{4}\sum_{k=1}^{4} \alpha_{jk}\, ln\,(K_{ij})\, ln\,(K_{ik}) + v_i - u_i \end{aligned} \quad (2)$$

where $ln\,(Y_i)$ is the logarithm of the citrus yield of farmer i; $ln\,(K_{ij})$ is the logarithm of the input factor j of farmer i; and $ln\,(K_{ij})^2$ is its squared term; $ln\,(K_{ij})\,ln\,(K_{ik})$ is the interaction term between inputs j and k and $j \neq k$. Following previous studies (Clemente et al., 2015; Ma et al., 2018; Zheng et al., 2021) and considering the characteristics of citrus production, we selected four input variables: fertilisers, pesticides, labour, and others. Fertilisers and pesticides refer to the expenditures on these two chemical inputs per unit area, measured in yuan/mu. Labour refers to the number of family labourers and hired labour for citrus production, measured in days/mu. Others refer to the expenditure on irrigation, physical, and biological pest management, measured in yuan/mu. v_i and u_i are specified in Equation (1). α_0 is a constant. α_j, α_{jj} and α_{jk} are parameters to be estimated.

3.3 Calculating technical efficiency scores

After estimating Equation (2), the technical efficiency scores of citrus production can be calculated as follows (DeLay et al., 2022; Zheng et al., 2021):

$$TE_i = \frac{Y_i}{Y_i^*} = e^{-u_i} \tag{3}$$

where TE_i is the technical efficiency score calculated for citrus farmer i; Y_i is the observed citrus yield; Y_i^* is the expected optimal citrus yield when all inputs are used efficiently; e^{-u_i} is the exponential function of the inefficiency term.

Next, we will estimate the impact of marketing contract choices on the technical efficiency of citrus production. By doing this, the technical efficiency scores calculated by Equation (3) will be used as a dependent variable.

3.4 Estimating the impacts of marketing contract choices on technical efficiency

3.3.1 Model selection

Farmers self-decide which type of marketing contracts they choose when selling citrus to the markets. Farmers' decisions about marketing contract choices are influenced by observed personal and socio-economic characteristics (e.g., age, gender, education, and household size) and unobserved characteristics (e.g., motivations and innate abilities). Thus, sample selection bias may exist, which should be addressed. The propensity score matching model has been widely used to solve this selection bias problem when the treatment variable is binary (Khan et al., 2022; Zhang et al., 2020). However, this model is inappropriate when there are more than two choices for the treatment variable. Although multivalued treatment effect models help to solve the problem of selectivity bias when there are more than two choices for the treatment variable (Issahaku and Abdulai, 2020; Ma et al., 2022; Tabe-Ojong et al., 2023), in nature, this approach cannot solve the selection bias caused by unobservable factors. In this study, we employ the MESR model to estimate the impact of marketing contract choices on the technical efficiency of citrus production. The MESR model helps to address the issue of selection bias arising from both observed and unobserved factors (Kassie et al., 2015; Khonje et al., 2018; Setsoafia et al., 2022).

3.3.2 MESR model

The MESR model is divided into three stages. In the first stage, the factors influencing farmers' decisions to choose different types of marketing contracts are analysed using a multinomial logit (MNL) model. In the second stage, the technical efficiency equations under different marketing contract choice scenarios are estimated by ordinary least squares regressions, in which the selectivity correction terms estimated in the first stage are included as extra regressors. In the third stage, the impacts of marketing contract choices on technical efficiency are calculated by estimating the average treatment effect on the treated (ATT).

In the first stage, we set up an MNL model to estimate the factors influencing farmers' decisions to choose different types of marketing contracts with the following Equation:

$$P_{ij} = Pr\ (\varepsilon_{ij} < 0|Z_i) = \frac{exp\ (Z_i\beta_j)}{\sum_{j=1}^{3} exp\ (Z_i\beta_j)}, j=1, 2, 3 \tag{4}$$

where P_{ij} denotes the probability that farmer i uses marketing contract j to sell their citrus, where j=1 for no contract users, j=2 for verbal contract users, and j=3 for written contract users; Z_i denotes a vector of individual, household, and farm-level characteristics and β_j is a vector of parameters to be estimated.

To consistently estimate the MESR model, at least one instrumental variable should be included in Z_i in Equation (4). In this study, we chose a dummy variable representing risk attitude as an instrumental variable. Specifically, the risk attitude variable equals 1 if farmer i is a risk lover and 0 otherwise. Theoretically, risk attitudes are correlated with marketing contract choices. Compared with product sales using written contracts, the sales at the spot markets involve uncertainties due to market fluctuations. The risk of contract breach for verbal contracts is higher than that for written contracts because the latter has a greater legal binding. These facts suggest that risk lowers are more likely to sell their products at the spot markets or using verbal contracts (Vassalos et al., 2016). Meanwhile, farmers' risk attitudes do not directly affect the technical efficiency of citrus production. We follow previous studies to statistically check the validity of the instrumental variable by using falsification tests (Ma et al., 2023b; Nnaji et al., 2022). The results (see Table A3 in the Appendix) show that the instrumental variable is correlated with the treatment variable (i.e. marketing contract choices) and uncorrelated with the outcome variable (i.e. technical efficiency score). The findings verify the appropriateness of the selected instrumental variable.

In the second stage, we analyse the technical efficiency score equations for different types of marketing contract users. The outcome equations for each possible regime j are specified:

$$\begin{cases} Regime\ 1\,(no\ contract\ users): & TE_{i1} = X_i\eta_1 + u_{i1}\ if\ j = 1 \\ Regime\ 2\,(verbal\ contract\ users): & TE_{i2} = X_i\eta_2 + u_{i2}\ if\ j = 2 \\ Regime\ 3\,(written\ contract\ users): & TE_{i3} = X_i\eta_3 + u_{i3}\ if\ j = 3 \end{cases} \quad (5)$$

where TE_{ij} $(j = 1, 2, 3)$ is the technical efficiency score of farmer i in regime j; X_i refers to a vector of exogenous variables (e.g., age, gender, and education) that may affect the technical efficiency score. Except for IV included in Z_i in Equation (4), X_i allows overlap with Z_i; η_j refers to the corresponding coefficients; u_{ij} refers to the error term with a conditional mean of zero mean.

In Equation (5), X_i helps to address the selection bias caused by observable factors. However, if selection bias issues are generated from unobservable factors, the estimated treatment effect of marketing contract choices on technical efficiency may still be biased. To address this unobserved selection bias issue appropriately, the MESR model predicts the selectivity correction terms after estimating Equation (4) and includes them as additional regressors in Equation (5). Then, Equation (5) can be rewritten as follows:

$$\begin{cases} Regime\ 1\,(no\ contract\ users): & TE_{i1} = X_i\rho_1 + \lambda_1\sigma_1 + \omega_{i1}\ if\ j = \\ Regime\ 2\,(verbal\ contract\ users): & TE_{i2} = X_i\rho_2 + \lambda_2\sigma_2 + \omega_{i2}\ if\ j \\ Regime\ 3\,(written\ contract\ users): & TE_{i3} = X_i\rho_3 + \lambda_3\sigma_3 + \omega_{i3}\ if\ j \end{cases} \quad (6)$$

where TE_{ij} and X_i have been defined previously; λ_1, λ_2, and λ_3 are vectors of selectivity correction terms (Jin et al., 2021; Tesfaye et al., 2021); ρ_j and σ_j denote the corresponding coefficients; ω_{ij} is the error term with an expectation of zero mean.

In the third stage, we calculate the ATT of marketing contract choices. We follow previous studies (Jin et al., 2021; Setsoafia et al., 2022) to estimate the ATT by comparing the expected outcomes of different contract users under actual and counterfactual scenarios. Without loss of generalisation, taking written contract users ($j = 3$) as an example, the observed technical efficiency score can be predicted as follows:

$$E\left(TE_{i3}|j=3\right)=X_i\rho_j+\lambda_j\sigma_j \tag{7}$$

In a counterfactual context, the control group for written contract users (i.e. treated group) could be either verbal or no contract users. The technical efficiency score for written contract users in a counterfactual context of no contract users can be predicted as follows:

$$E\left(Y_{i3}|j=1\right)=X_i\rho_1+\lambda_j\sigma_1 \tag{8}$$

Finally, ATT can be calculated as the difference between Equation (7) and Equation (8):

$$ATT=E\left(Y_{i3}|j=3\right)-E\left(Y_{i3}|j=1\right)=X_{ij}\left(\rho_j-\rho_1\right)+\lambda_j\left(\sigma_j-\sigma_1\right) \tag{9}$$

4 Data and descriptive statistics

4.1 Data

Data used in this study were collected from a survey of citrus farmers conducted between October and November 2022 in Jiangxi Province, China. The collected information refers to 2021 citrus production. We used a multi-stage stratified random sampling technique to select the samples. First, we purposively selected Ganzhou and Fuzhou cities as the survey sites because they are major citrus-producing areas in Jiangxi Province. Second, seven townships were randomly selected from each sampled city. Third, approximately four villages were randomly selected in each township based on the size and population of the villages. Fourth, 10-30 farmers were randomly selected in proportion to the population of each village. Finally, we obtained 1,009 samples. During data cleaning, we deleted 127 samples that had incomplete information. As a result, our final sample comprises 882 samples, including 294 written contract users, 255 verbal contract users, and 333 no-contract users.

We prepared a well-structured questionnaire to conduct a face-to-face survey of citrus farmers. The questionnaire covers a rich of information on farmers' characteristics at the individual level (e.g., gender, age, and personal experience), the household level (e.g., family size, household income, and asset ownership), and the production and marketing level (e.g., production inputs, area, and production volume). The survey was helped by enumerators who are postgraduate students majoring in agricultural and economics management at an agricultural university in central China. Before the formal survey, we conducted a pre-survey in July 2022 to collect feedback from citrus farmers and modify the survey questionnaire. The presurvey increases collected information on citrus farmers' production and marketing reliability and validity.

4.2 Descriptive statistics

Table 1 shows the descriptive statistics of the variables used in the production function. The average citrus yield was 1,183 kg/mu. Regarding the input variables, citrus farmers spent, on average, 1,102 yuan/mu on fertilisers and 608 yuan/mu on pesticides. The number of labourers used in citrus production was 49.71 days/mu. Expenditures on other inputs were 266 yuan/mu on average.

[Insert Table 1 here]

Table 2 presents the descriptive statistics of the variables used in the MESR model. Around 33% of citrus farmers used written contracts, and 29% used verbal contracts. Appropriately, 38% of citrus farmers did not use any marketing contracts (i.e. spot market sales). Table 2 also presents that the average age of citrus farmers in our sample was 53.28 years. Most farmers (78%) in our sample were males, and they received an education between primary school and junior middle school. The average household size was 5.12 members, and the workforce ratio was 63%. The average annual household income was 34,780 yuan/capita. The average farm size was 20.5 mu, comprising an average of 2.71 plots. The average number of farming years was 19.44 years, and the average number of fruiting years of citrus was 7.36 years. The average distance from the selected villages to the nearest county was 18.28 km.

[Insert Table 2 here]

Table 3 presents the mean differences in the control variables between written, verbal, and no-contract users. The last three columns of Table 3 present the pairwise comparisons in mean differences. For the sake of simplicity, we discuss the mean differences between written and no-contract users (i.e. the fifth column). The results reveal that compared to no-contract users, written contract users were more likely to be male, better educated, and have larger family sizes and higher household incomes. Besides, written contract users had shorter farming years and experienced shorter citrus-fruiting years than their no-contract user counterparts. The information presented in Table 3 confirms that written, verbal, and no-contract users are systematically different in observed characteristics, suggesting they self-decide (i.e. self-selection) which type of marketing contracts they choose. Thus, it is necessary to address the selection bias issues when estimating the effect of marketing contract choices on the technical efficiency of citrus production. As discussed, this study relies on the MESR model to tackle selection bias issues.

[Insert Table 3 here]

5 Results and discussion

5.1 Production frontier

The results estimated for the production function are shown in Table A2 in the Appendix. As mentioned earlier, we should use the Translog functional form with an exponential distribution assumption for the error term to estimate the production function. The results (see the last column of Table A2) present that the first-order coefficient of the fertiliser variable is negative and significant, suggesting that an increase in fertiliser expenditure would decrease citrus yield. This is not impossible. Fertiliser is a productivity-enhancing input, so farmers may overuse fertilisers to increase citrus output. Studies focusing on China have reported that it is common for Chinese farmers to overuse fertilisers in agricultural production (Ren et al., 2021; Sun et al., 2019; Yu et al., 2023). However, the overuse of fertilisers would harm citrus production in different ways, such as seedling burnt, fruit and leaf wilting, and soil consolidation and degradation, resulting in yield loss. In their study for Ireland, Buckley and Carney (2013) concluded that the overuse of fertilisers increases economic and environmental costs and is not conducive to maximising crop yields.

5.2 Technical efficiency scores

Table 4 summarises the average technical efficiency score of citrus production, calculated based on Equation (3). It shows that the average technical efficiency score of citrus production is 0.646, with a standard deviation of 0.170. The finding suggests that citrus farmers can increase citrus yield by 35% if they use the current production inputs and technologies more efficiently. Our finding suggests a relatively lower technical efficiency score than Carrer et al. (2015), who calculated the technical efficiency score of citrus farms in Brazil and reported a value of 0.752. Further, the minimum and maximum technical efficiency scores were 0.021 and 0.892, respectively.[2] The findings suggest large variations in technical efficiency scores exist among citrus farmers. In other words, citrus farmers have used their production inputs heterogeneously. Citrus production is technology demanding regarding pruning, soil and water conservation, the selection of appropriate fertilisers and pesticides and the time and ways to apply them (Beltrán-Esteve and Reig-Martínez, 2014). Lack or inappropriate use of production technologies would result in losses in production efficiency.

[Insert Table 4 here]

Figure 2 depicts the distributions of technical efficiency scores. It shows that most citrus farmers (69.16%) received higher technical efficiency scores than 0.6. Around 2.61% of citrus farmers received technical efficiency scores lower than 0.2, and 8.05% of their counterparts received the same, between 0.2 and 0.4. Besides, around 178 citrus farmers (i.e. 20.18%)

[2] In the study of Carrer et al. (2015), the technical efficiency scores range between 0.28 and 0.97.

received technical efficiency scores between 0.4 and 0.6.

[Insert Figure 2 here]

5.3 Factors influencing marketing contract choices

Table 5 presents the results of the first stage estimation of the MESR model, demonstrating the factors influencing citrus farmers' choices to use different types of marketing contracts. Because the coefficient estimates of the MNL model are not intuitive in interpretation, we calculate the marginal effects of the variables for better understanding. The Wald test in the lower part of Table 5 is significant, indicating that the null hypothesis that all regression coefficients are jointly equal to zero is rejected.

The second column of Table 5 shows the results for the written contract specification. The marginal effect of the production condition variable is negative and significant, suggesting that citrus farmers reporting better production conditions such as good soil, road, and irrigation are 3.7% less likely to use written contracts. Farmers choose to use written contracts to stabilise their product sales and reduce market uncertainties, while markets are usually better developed in those places with better production conditions. Thus, farmers endowed with better production conditions tend to rely less on written contracts. The marginal effect of plot number is significantly negative, suggesting that the larger number of plots is associated with a lower probability of using written contracts. Producing citrus on scattered plots increases product heterogeneity, while buyers prefer products with homogenous attributes regarding colour, shape and suger context. Therefore, scatted citrus production reduces the likelihood of written contract sales. The number of disaster occurrences significantly and positively affects written contract usage. Disasters reduce the citrus output and its quality, hampering the citrus sales. Therefore, farmers who experienced natural disasters prefer using written contracts to reduce sales uncertainties. The marginal effect of the distance variable is significantly negative, indicating that the further distance from farmers' residing villages to the nearest country, the less likely farmers use written contracts. An increased distance between the village and the nearest county increases the transaction costs, resulting in a lower likelihood of written contract sales. The risk attitude variable's significant and negative marginal effect suggests that risk lovers are less likely to use written contracts.

[Insert Table 5 here]

The third column presents the results for the verbal contract specification. The marginal effect of the education variable is significantly positive, indicating that better-educated farmers are more likely to use verbal contracts. Education improves farmers' communication and negotiation skills, helping build social trust between farmers and buyers and facilitating the establishment of a verbal contract agreement (Rondhi et al., 2020). The marginal effect of the farm size variable is positive and significant, indicating that a 1% increase in farm size would increase the probability of selling citrus using the verbal contract by 0.1%.

The fourth column shows the results for the no-contract specification. The marginal effect on the plot number is significantly positive, suggesting that larger plots used for citrus production are associated with a higher probability of using spot market sales (i.e. no contract). As discussed previously, fragmented plots produce a mixed-quality product, while buyers prefer products with homogeneous attributes. Thus, farmers producing citrus on scatted farmland tend to sell their products at the spot markets.

5.4 Factors determining the levels of technical efficiency

Table 6 presents the results of the second-stage estimations of the MESR model. The lower part of Table 6 shows the selection correction terms, λ_1, λ_2, and λ_3, are significant, suggesting the presence of unobservable selection bias. Therefore, estimating the MESR model in the present study is appropriate.

The results indicate that individual, household, and production characteristics significantly affect the technical efficiency of different types of marketing contract users. For example, the coefficient of the education variable is significantly positive in the second column of Table 6. The finding suggests that better-educated written contract users obtain higher technical efficiency. Education helps improve written contract users' understanding of the product attributes required by the market buyers and enables them to manage their orchards better to meet those requirements, which finally contributes to an increase in technical efficiency. Farm size significantly and positively affects the technical efficiency of written contract users (see column 2 of Table 6), a finding consistent with the existing studies (Dessale, 2019; Zhang et al., 2023). Cultivating citrus orchards with larger farm sizes, due to economies of scale, improves input use efficiency and saves production costs, finally increasing technical efficiency.

[Insert Table 6 here]

The significantly positive coefficient of the gender variable in column 3 of Table 6 indicates that male verbal contract users tend to achieve a higher level of technical efficiency than female verbal contract users. The finding is largely in line with the findings reported in the previous studies (Danso-Abbeam et al., 2020). The coefficient of plot number is significantly positive (see column 3 of Table 6), suggesting that verbal contract users cultivating citrus on a larger number of plots obtained a higher level of technical efficiency. On the one hand, land fragmentation is detrimental to farm production (Ali et al., 2019; Martey et al., 2019). On the other hand, farmers can operate precise farm management on scattered farmland, increasing production efficiency. Previous studies have found a positive relationship between precision agriculture adoption and technical efficiency (Carrer et al., 2022; DeLay et al., 2022). The fourth column shows the results for the no-contract specification. The significantly positive coefficient of household income indicates that an increase in household income increases the technical efficiency of no-contract users.

Adequate income enables no-contract users to purchase yield-enhancing inputs such as fertilisers and pesticides, improving production efficiency.

5.5 Treatment effects of marketing contract choices on technical efficiency

Table 6 presents the results of the third stage of the MESR model, showing the ATT on technical efficiency for different types of marketing contract users. In general, the results show that relative to no-contract sales, the usage of written and verbal contracts improves the technical efficiency of citrus production, and written contracts greatly affect technical efficiency. Specifically, the average technical efficiency scores for written and verbal contract users are 14% and 2% higher than those for no-contract users. The average technical efficiency score for written contract users is 8% higher than for verbal contract users. Previous studies have shown that using marketing contracts helps improve farm economic performance (Haji, 2010; Ma and Abdulai, 2016; Oe et al., 2004; Ruml and Qaim, 2020). Our findings add new insights to the literature that using marketing contracts helps improve technical efficiency, contributing to productivity improvement and food security.

[Insert Table 6 here]

6 Conclusions and policy implications

Marketing contracts are important institutional arrangements in agricultural value chains because they reduce farmers' marketing risks and stabilise market supply. Although several studies have analysed the income effects of marketing contracts, little is known about whether marketing contracts impact production efficiency. This question merits attention. Marketing contract users must meet the product attributes required by the market buyers, so their production behaviour in input application and farm management might differ from those who prefer spot market sales. This fact leads to potential differences in technical efficiency between marketing contract users and non-users. Therefore, this paper analysed the effect of marketing contracts on technical efficiency, considering written contracts, verbal contracts, and no contracts. We combine the stochastic frontier model with the multinomial endogenous switching regression model to empirically analyse the data collected from citrus producers in Jiangxi Province, China.

Our results showed that the mean technical efficiency score of citrus production was 0.646, highlighting that citrus farmers can increase citrus yield by 35% if they can use the current production inputs and technologies more efficiently. Using written and verbal contracts had different impacts on the technical efficiency of citrus production. Specifically, average technical efficiency scores for written and verbal contract users were 14% and 2% higher than those for no-contract users. The average technical efficiency score for written contract users was 8% higher than for verbal contract users. Regarding the factors influencing farmers' decisions to use marketing contracts, our estimates showed that farmers who experienced natural disasters were more likely to use written contracts. At the same time, those endowed with better education, larger farm sizes, and better production conditions were more likely to use verbal contracts.

Our findings have significant policy implications. The findings of the positive relationship between marketing contract use and technical efficiency of citrus production highlight the importance of promoting marketing contracts among smallholder farmers. In particular, the usage of written contracts should be widely promoted as it has a larger impact on technical efficiency than verbal contracts. In practice, by collaborating with rural farmer organisations, the government should organise workshops and trainings to help strengthen farmers' understanding of the benefits of marketing contract use when selling their products. Land fragmentation increases product heterogeneity, which prevents farmers from using marketing contracts. Therefore, the government should further promote land consolidation through land transfer, which can benefit economies and specialisation production scales, improving product sales with marketing contracts.

Although the findings of this study are quite interesting, due to data limitations, we could not explore the mechanisms through which marketing contracts affect the technical efficiency of citrus production. We believe this would be an interesting area to be explored in the future. Besides, future studies should extend the findings of this study by analysing data collected from other high-value crops to help generalise our findings.

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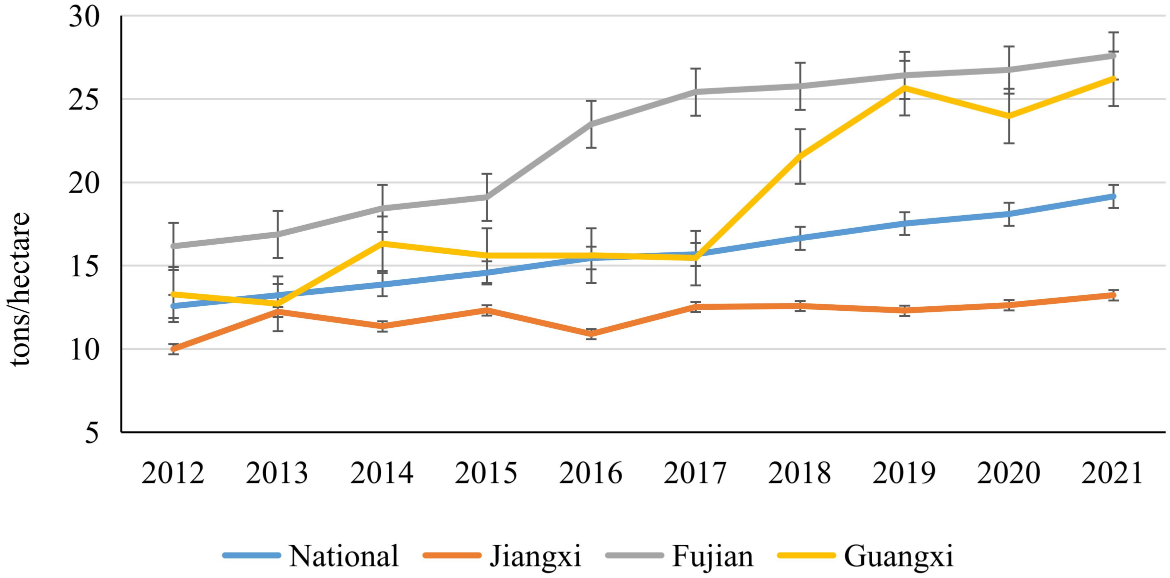
Figures



Source: China Rural Statistical Yearbooks (2013-2022)

Figure 1 Major citrus-producing provinces by output per unit area in 2021

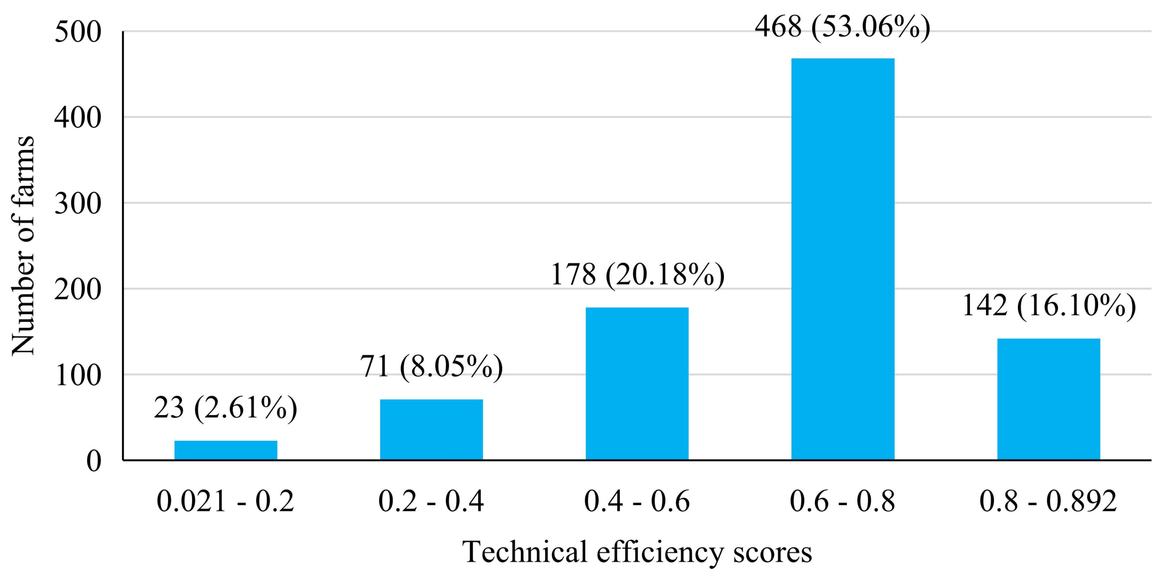


Figure 2 Distributions of technical efficiency scores and sample size

Tables

Table 1 Variables used in the production function and summary statistics

Variables	Measurements	Mean (S.D.)
Citrus yield	(100 kg/mu) [a]	11.83 (8.87)
Fertilisers	Expenditures on fertilisers (100 yuan/mu) [b]	11.02 (6.40)
Pesticides	Expenditures on pesticides (100 yuan/mu)	6.08 (4.56)
Labour	Number of family labourers and hired labourers (days/mu)	49.71 (53.25)
Others	Expenditures on other inputs (e.g., irrigation, physical and biological pest management) (100 yuan/mu)	2.66 (2.60)
Observations		882

Note: S.D. refers to the standard deviation; [a] 1 mu=1/15 hectare; [b] Yuan is a Chinese currency (1 USD=6.73 yuan in 2022)

Table 2 Variables used in the MESR model and summary statistics

Variables	Measurements	Mean (S.D.)
Dependent variable		
Technical efficiency	Calculated by Equation (3)	0.65 (0.17)
Treatment variables		
Written contracts	1 If a farmer uses a written contract when selling citrus, 0=otherwise	0.33 (0.47)
Verbal contracts	1 If a farmer uses a verbal contract when selling citrus, 0=otherwise	0.29 (0.45)
No contracts	1 If a farmer did not use any type of contract when selling citrus, 0=otherwise	0.38 (0.49)
Control variables		
Age	Age of household head (HH) in years	53.28 (9.47)
Gender	1 if HH is male, 0 otherwise	0.78 (0.41)
Education	The education level of HH [a]	2.69 (1.03)
Family size	Number of people residing in a household in persons	5.12 (1.84)
Workforce ratio	Ratio of household members over the age of 15 and under the age of 60	0.63 (0.27)
Household income	(10,000 yuan/capita/year)	3.48 (4.26)
Farm size	Size of farmland (mu)	20.50 (41.46)
Farming years	Number of years HH engaged in citrus farming (years)	19.44 (9.32)
Production conditions	Farmers' self-reported production conditions in terms of soil, road, and irrigation: from 1=very poor to 5=very good	3.35 (0.85)
Plot number	Number of citrus plots	2.71 (2.56)
Fruiting years	Number of citrus-fruiting years	7.36 (6.56)
Disaster occurrences	Number of serious natural disasters suffered (times)	2.87 (1.44)
Distance	Distance from the village to the nearest county (km)	18.28 (14.55)
Location	1 if HH resides in Ganzhou, 0 otherwise (i.e., Fuzhou)	0.50 (0.50)
Instrumental variable		
Risk attitude	1 if HH is a risk-lover, 0 otherwise	0.23 (0.42)
Observations		882

Note: S.D. refers to the standard deviation; [a] 1=illiterate; 2=Primary school; 3=Junior middle school; 4=High school/technical school; 5=College and above

Table 3 Mean difference in the selected variables between written contracts, verbal contracts, and no contracts

Variables	Written contract users (W)	Verbal contract users (V)	No-contract users (N)	Mean differences		
				W vs. N	W vs. V	V vs. N
Age	53.47	52.72	53.53	-0.07	0.74	-0.81
Gender	0.84	0.75	0.76	0.08***	0.09**	-0.00
Education	2.80	2.77	2.54	0.26***	0.03	0.23***
Family size	5.31	5.11	4.95	0.36**	0.20	0.16
Workforce ratio	0.62	0.62	0.66	-0.04*	-0.00	-0.04
Household income	3.69	3.65	3.16	0.53*	0.05	0.49
Farm size	21.37	25.61	15.81	5.56**	-4.25	9.81**
Farming years	17.02	19.73	21.35	-4.34***	-2.71***	-1.63**
Production conditions	3.36	3.44	3.27	0.10	-0.08	0.17**
Plot number	1.93	2.48	3.56	-1.63***	-0.55***	-1.08***
Fruiting years	4.90	8.14	8.93	-4.03***	-3.24***	-0.80
Disaster occurrences	2.89	2.83	2.89	-0.01	0.06	-0.07
Distance	18.59	18.46	17.88	0.71	0.13	0.57
Location	0.75	0.41	0.34	0.41***	0.34***	0.07*
Risk attitude	0.14	0.25	0.29	-0.16***	-0.11***	-0.05
Observations	294	255	333			

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

Table 4 Summary of technical efficiency

Mean	S.D.	Min.	Max.
0.646	0.170	0.021	0.892

Table 5 Marginal effects of selected variables on marketing contract choices: First stage estimation of the MESR model

Variables	Written contracts	Verbal contracts	No contracts
Age	0.002 (0.002)	-0.001 (0.002)	-0.000 (0.002)
Gender	0.016 (0.040)	-0.041 (0.039)	0.024 (0.040)
Education	-0.009 (0.016)	0.027 (0.016)*	-0.018 (0.017)
Family size	0.007 (0.008)	0.003 (0.008)	-0.010 (0.009)
Workforce ratio	0.034 (0.059)	-0.097 (0.061)	0.062 (0.062)
Household income	0.006 (0.005)	-0.005 (0.005)	-0.001 (0.007)
Farm size	-0.000 (0.001)	0.001 (0.001)*	-0.001 (0.001)
Farming years	-0.003 (0.002)	0.001 (0.002)	0.002 (0.002)
Production conditions	-0.037 (0.018)**	0.045 (0.018)**	-0.009 (0.020)
Plot number	-0.021 (0.012)*	-0.017 (0.008)**	0.038 (0.008)***
Fruiting years	-0.001 (0.003)	0.002 (0.003)	-0.002 (0.003)
Disaster occurrences	0.017 (0.010)*	-0.014 (0.011)	-0.003 (0.012)
Distance	-0.002 (0.001)**	0.001 (0.001)	0.001 (0.001)
Location	0.262 (0.043)***	-0.141 (0.042)***	-0.121 (0.043)***
Risk attitude	-0.174 (0.036)***	0.048 (0.036)	0.126 (0.035)***
Sample size	882	882	882
Joint Wald χ2 (30)	172.47***		
Log-likelihood	-859.7944		

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; Standard errors in parenthesis.

Table 6 Determinants of technical efficiency by marketing contract types: Second stage estimation of the MESR model

Variables	Written contracts	Verbal contracts	No contracts
Age	-0.000 (0.002)	0.001 (0.006)	0.002 (0.001)
Gender	-0.070 (0.054)	0.090 (0.032)***	-0.030 (0.025)
Education	0.024 (0.010)**	-0.063 (0.055)	-0.012 (0.020)
Family size	0.001 (0.017)	-0.015 (0.008)**	-0.019 (0.005)***
Workforce ratio	-0.072 (0.068)	0.204 (0.132)	0.010 (0.050)
Household income	-0.006 (0.005)	0.013 (0.013)	0.005 (0.002)**
Farm size	0.002 (0.001)**	-0.002 (0.002)	0.000 (0.000)*
Farming years	0.000 (0.003)	0.003 (0.007)	0.001 (0.002)
Production conditions	0.011 (0.058)	-0.064 (0.042)	-0.004 (0.017)
Plot number	-0.013 (0.017)	0.049 (0.023)**	0.016 (0.009)*
Fruiting years	0.016 (0.002)***	-0.000 (0.005)	0.002 (0.002)
Disaster occurrences	-0.012 (0.005)**	0.030 (0.027)	0.006 (0.007)
Distance	0.001 (0.001)	-0.001 (0.002)	0.001 (0.001)*
Location	-0.040 (0.201)	0.130 (0.200)	-0.107 (0.049)**
Selectivity correction terms			
λ_1	-0.415 (0.643)	0.823 (0.986)	-0.266 (0.137)*
λ_2	0.515 (0.638)	-0.659 (0.293)**	-0.824 (0.362)**
λ_3	-0.043 (0.264)	0.236 (0.910)	-0.675 (0.349)*
Constant	0.676 (0.189)***	1.589 (0.834)*	0.253 (0.197)
Sample size	882	882	882

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; Standard errors in parenthesis.

Table 7 Results of the treatment effects estimations: MESR model

Actual		Counterfactual		ATT	*t*-value	Change
Written	0.650 (0.004)	No	0.570 (0.006)	0.081 (0.004)***	19.069	14%
Verbal	0.650 (0.005)	No	0.637 (0.006)	0.013 (0 .004)***	3.574	2%
Written	0.650 (0.004)	Verbal	0.604 (0.005)	0.047 (0.004)***	11.492	8%

Note: *** p < 0.01 and ** p < 0.05; Standard errors in parenthesis.

Appendix

Table A1 Estimation results of Cobb-Douglas function

	Half-normal	Truncated-normal	Exponential
Ln (Fertilizers)	0.005 (0.050)	-0.009 (0.050)	-0.009 (0.050)
Ln (Pesticides)	0.154 (0.034)***	0.163 (0.034)***	0.163 (0.034)***
Ln (Labour)	0.112 (0.030)***	0.112 (0.029)***	0.112 (0.029)***
Ln (Others)	0.108 (0.027)***	0.110 (0.027)***	0.110 (0.027)***
Constant	2.299 (0.147)***	2.047 (0.147)***	2.047 (0.147)***
$\sigma(u)$	1.033 (0.055)***	20.64 (27.02)	0.550 (0.042)***
$\sigma(v)$	0.441 (0.033)***	0.532 (0.027)***	0.532 (0.027)***
λ	2.339 (0.081)***	38.783 (27.02)	1.032 (0.063)***
Log-likelihood	-989.316	-982.9368	-982.9304

Note: *** $p < 0.01$; Standard errors in parenthesis.

Table A2 Estimation results of the Translog function

	Half-normal	Truncated-normal	Exponential
Ln (Fertilizers)	-1.023 (0.395)***	-1.029 (0.387)***	-1.029 (0.387)***
Ln (Pesticides)	-0.293 (0.230)	-0.312 (0.230)	-0.312 (0.230)
Ln (Labour)	-0.162 (0.189)	-0.184 (0.183)	-0.184 (0.183)
Ln (Others)	0.158 (0.183)	0.097 (0.182)	0.096 (0.182)
Ln (Fertilizers) * Ln (Pesticides)	0.241 (0.147)	0.239 (0.148)	0.239 (0.148)
Ln (Fertilizers) * Ln (Labour)	0.195 (0.136)	0.182 (0.131)	0.182 (0.131)
Ln (Fertilizers) * Ln (Others)	0.006 (0.120)	0.046 (0.120)	0.046 (0.120)
Ln (Pesticides) * Ln (Labour)	-0.007 (0.092)	-0.009 (0.090)	-0.009 (0.090)
Ln (Pesticides) * Ln (Others)	0.012 (0.082)	-0.003 (0.081)	-0.003 (0.081)
Ln (Labour) * Ln (Others)	-0.047 (0.077)	-0.029 (0.075)	-0.029 (0.075)
0.5 * Ln $(\text{Fertilizers})^2$	0.189 (0.150)	0.190 (0.151)	0.190 (0.151)
0.5 * Ln $(\text{Pesticides})^2$	0.121 (0.074)	0.146 (0.075) *	0.146 (0.075) *
0.5 * Ln $(\text{Labour})^2$	0.018 (0.043)	0.028 (0.042)	0.028 (0.042)
0.5 * Ln $(\text{Others})^2$	0.015 (0.042)	0.017 (0.043)	0.017 (0.043)
Constant	4.268 (0.622)***	4.091 (0.611)***	4.090 (0.611)***
$\sigma(u)$	1.017 (0.054)***	20.629 (28.31)	0.549 (0.041)***
$\sigma(v)$	0.435 (0.032)***	0.517 (0.026)***	0.517 (0.026)***
λ	2.336 (0.080)***	39.920 (28.31)	1.063 (0.061)***
Log-likelihood	-976.369	-968.3652	-968.3568

Note: *** p < 0.01, * p < 0.1; Standard errors in parenthesis.

Table A3 Falsification test of the selected instrumental variable.

	Statistics	*p*-value
Marketing contracts	$\chi 2$-value=21.86***	0.001
Technical efficiency score	*F*-value= 0.06	0.802

Note: *** p < 0.01.