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The impact of market-oriented cooperation on food production performance in small-scale farms in rural China

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Introduction: Small-scale farmers in developing countries can significantly contribute to sustainable food production through market-oriented cooperation (MOC). MOC allows farmers to access machinery services and specialized labor, but it also carries economic costs that may impact food production performance in small-scale farms. This study attempts to uncover the association between farmers' MOC participation and food production performance in small-scale farms in rural China, using a sample of 650 rice farmers in Jiangsu province.

Methods: We applied the stochastic frontier analysis to calculate the technical efficiency that indicates the production performance of small-scale farms. The treatment effect model is employed to detect the effect of farmers' MOC participation on technical efficiency, and the multivalued treatment effects model is used to explore the relationship between farmers' intensity of MOC and technical efficiency.

Results: The results show that farmers' MOC participation significantly increases technical efficiency of small-scale farms, with an inverted U-shaped correlation between MOC participation intensity and technical efficiency. A heterogeneity analysis based on production phases reveals that farmers tend to adopt MOC in machinery-driven phases with higher priority than in labor-driven phases. MOC in labor-driven phases, such as seedling and spraying, presents negative effect on technical efficiency.

Discussion: These findings highlight the crucial role of MOC in food production performance in small-scale farms, and provide insights for designing MOC strategies in different production phases in order to facilitate sustainable food production in developing regions. This research addresses the need for solutions to improve food production sustainability under agricultural transformation in developing countries. It also touches on the challenges and opportunities that producers face in adopting new practices and participating in the modern food supply chain.

KEYWORDS

sustainable food production, market-oriented cooperation, efficient resource utilization, small-scale farms, food production performance, treatment effect model

1. Introduction

Market transactions can boost the economic development of rural areas. However, many developing countries have a long history of self-sufficient agricultural production based on small-scale farms. In these countries, agricultural transformation has become increasingly important for securing the sustainable supply of national food and economic growth. It is believed that much potential still exists for the improvement of agricultural production efficiency in developing regions (Henderson and Isaac, 2017). Hence, enhancing efficiency through the market may contribute to the sustainability of food production. In the context of self-sufficient production, small-scale farmers usually choose to increase the input of family labor in agriculture as such labor-intensive cultivation can reduce the explicit labor cost and implicit supervision cost (Ma et al., 2022). Also, existing constraints may hinder farmers' integration with agricultural markets, such as agricultural credit (Li and Huo, 2021; Rashid, 2021; Chen Z. et al., 2022; Kassouri and Kacou, 2022), production technology (Yang et al., 2020; Mao et al., 2021; Ruzzante et al., 2021), and information communication (Yang et al., 2021; Zheng et al., 2021; Zheng Y. et al., 2022). However, it has been recognized that farmers' participation in the agricultural market can promote a profound transformation of agricultural production, secure the sustainability of food production, and improve the livelihoods of small-scale farmers (Barrett, 2008; Liu et al., 2021).

In this study, market-oriented cooperation (MOC) is defined as the production mode in which farmers seek agricultural machinery services or employ labor according to their needs at different production phases. These are fundamental approaches to alleviate the shortage of agricultural resources in farmer households in developing countries. With about 0.5 billion small-scale farmers in rural areas, China has launched a series of agricultural reform initiatives, such as increasing subsidies for agricultural machinery and promoting agricultural outsourcing services (Lopez et al., 2017; Zhang et al., 2017; Mi et al., 2020). Conventionally, Chinese small-scale farmers cooperate with their relatives or neighbors through social networks in agricultural production. The cooperation is characterized by reciprocity among farmer households, and no explicit exchange of money is involved in the activity. With the enlightenment of market awareness in rural China, the belief is gaining ground that market forces make agricultural cooperation easier. Under the high seasonal requirement for agricultural production, MOC is much more flexible for farmers to seek labor force or other agricultural resources through the market. It can be more effective for realizing agricultural mechanization and reducing sunk costs than farmers' self-purchased machinery (Zhou et al., 2020; Zheng H. et al., 2022). Besides, MOC among farmers is useful to overcome labor shortages caused by migration and aging problems in rural areas. Farmers' cooperation based on the market system has become an essential approach to achieving agricultural modernization in developing regions.

The effect of farmers' MOC on the production performance of farms remains ambiguous. Some argued that MOC exerted a positive effect on agricultural production performance (Liu et al., 2021; Zhang et al., 2021), while others insisted on a negative effect (Qiu and Luo, 2021). Thus, this study attempts to clarify the role of MOC in sustainable food production, using the case of rice production in rural China. Different types of MOC were discussed in existing studies, indicating that agricultural resources can be equipped with market transactions to facilitate farmers (Zhang et al., 2021). For example, agricultural machinery services are mainly considered the key to improving production performance in rural areas (Yang et al., 2013; Takeshima, 2018; Qing et al., 2019; Qian et al., 2022). However, MOCs are not facilitated with complete mechanization in all production phases. The role of labor employment in MOC has not received enough attention. In China, labor employment has also been one of the indispensable ways for small-scale farmers to participate in MOC. Thus, it provides an opportunity to explore the role of MOC in both labor employment and machinery services. In some production phases, small-scale farmers can avoid the sunk costs of self-purchased machinery through MOC (Sheng et al., 2017), but the high cost of agricultural machinery services is likely to drive smallholders out of agriculture (Qiu and Luo, 2021). When farmers can employ laborers in particular production phases through MOC, the tendency of employees to shirk has reinforced the necessity of supervision in agricultural production (Eswaran and Kotwal, 1986). Despite the fact that agricultural market-oriented services can increase return to scale and agricultural productivity, the opportunism caused by incomplete contracts can still increase the losses and supervision costs of farmers' participation in MOC. These costs caused by the participating market are regarded as transaction costs (Coase, 1937). They may restrict access to markets for smallholders and accelerate poverty (Picazo-Tadeo and Reig-Martínez, 2006). Higher intensity of MOC based on small-scale farms is likely to result in economic inefficiency (Shi et al., 2021). Farmers' high inputs in MOC are not necessarily translated into high outputs as expected. To sum up, although MOC can help farmers with a labor shortage and a low level of mechanization, it makes farmers bear high transaction costs. Thus, the first objective of this study is to uncover the relationship between farmers' participation intensity of MOC and the production performance of small-scale farms. We employed the multivalued treatment effect model to evaluate the effect of farmers' intensity in MOC on the production performance of small-scale farms (Zhou and Ma, 2022). IPWRA and AIPW estimators are used to test the robustness of the estimation results.

To better understand cause and effect between MOC and production performance, the second objective of this study is to analyze the heterogeneous effects of MOC in different production phases. From the perspective of the production phase, rare studies examined the influence of MOC in the entire production process (Sun et al., 2018; Qu et al., 2021). Scholars may get contradictory results from investigating the impact of MOC in different production phases. In certain production phases, farmers can observe the phase progress and quality easily (e.g., plowing), while employees have rough rides to implement opportunistic behavior. However, it is not always the case in different production phases. Evidence suggests that rice yields are not significantly increased with pest control through MOC (Sun et al., 2018). In addition, the machinery harvesting service increases rice farmers' losses (Wu et al., 2017; Qu et al., 2020), showing a negative impact of MOC on production performance. Technical efficiency may be increased due to the high utilization efficiency of inputs, while it may be reduced due to ineffective inputs, such as the supervision costs caused by a moral hazard (Henderson and Isaac, 2017). Previous studies have rarely considered the heterogeneity of MOC in different agricultural production phases. Whether farmers' preferences for MOC are distinct in different production phases? What are the effects of MOC in different production phases on the production performance of small farms? This study attempts to answer the questions based on the case of rice farmers in rural China.

This study may contribute to the existing literature in the following aspects. First, different from prior studies, the MOC covers agricultural mechanization services and labor services in rural markets. It enables us to elaborate on the effects of distinct types of market transactions on the food production performance of small-scale farmers. Second, the possible negative side of MOC has been rarely considered. The increase in costs in MOC may decrease the food production performances of small-scale farms. Farmers' higher participation intensity in MOC requires higher input costs. It can be a barrier to food production performance. This study employs a multivalued treatment effect model (TEM) to analyze the impact of participation intensity in MOC on the production performance of small-scale farmers. Third, we conducted a heterogeneous analysis of the effect of MOC in different production phases. It is conducive to

TABLE 1 Descriptive statistics of input–output indicators of rice farmers.

Variable	Mean	Std. dev.	Min	Max	Unit
Ln (yield)	8.724	1.411	5.485	13.567	Ln (catty)
Ln (land)	1.969	1.195	0.182	6.396	Ln (mu)
Ln (labor)	3.801	1.201	0.000	9.131	Ln (days)
Ln (capital)	7.994	1.706	4.808	13.894	Ln (yuan)
Ln (technology)	6.334	2.026	0.000	11.678	Ln (yuan)

1 catty = 0.5 kg, 1 mu =1/15 hectare.

understanding farmers' preferences for MOC and its association with food production performances.

The rest of the study is organized as follows. In Section 2, we introduced the estimation strategies of the study. Section 3 presents data and descriptive statistics. The empirical results and discussion are reported in Section 4. We summarized the main conclusions and put forward recommendations in Section 5.

2. Materials and methods

2.1. Data and descriptive statistics

2.1.1. Data source

The data used in this study were obtained from the China Land Economic Survey (CLES) conducted by Nanjing Agricultural University in 2020. The database focuses on the rural land market, agricultural production, ecological environment, and other contents. The sampling method was as follows. First, 26 counties were selected within 13 municipalities in Jiangsu Province by the probability proportionate to size (PPS) sampling method. Second, two sample townships were selected from each county, and one administrative village was selected from each township. Finally, 50 households were sampled within each administrative village. The database contains about 2,600 farmers. Among them, rice farmers were selected as the case of this study because rice is the staple food in China and is grown by almost all sample farmers. After excluding the missing data, the valid sample consisted of 650 rice farmer households.

2.1.2. Variables and descriptive analysis

In the study, we used technical efficiency to represent the production performances of rice farmers. Following the previous studies (Zheng et al., 2021; DeLay et al., 2022; McFadden et al., 2022; Tirkaso and Hailu, 2022), we considered the total rice yield of a farm household as the output indicator and selected four input indicators, including the following components: (1) Capital, (2) Labor, (3) Land, and (4) Technology. Specifically, capital includes the cost of seeds, fertilizers, pesticides, water, electricity, and other expenses. Labor refers to the effort (days) spent by farmers in rice production. Land refers to the land area of rice cultivation of each farmer household. Technology refers to the cost of machinery, including direct use costs and indirect costs of maintenance. The summary of statistics for indicators is given in Table 1. It is important to note that farmers with full MOC in the whole production cycle do not input family labor or self-purchase machinery for rice production. The zero values of input indicators, such as labor, cannot be directly logarithmic. All zero values need to be replaced with one (Ma et al., 2018).

Table 2 presents the definition and descriptive statistics of the variables in this study. There are two independent variables under question in this study. The first is farmers' binary choices of participation in MOC for rice production. If the household has adopted MOC in any agricultural phase, the value of the participation decision is set to 1, otherwise it is set to 0. The second is farmers' participation intensity, measured by the number of production phases in which farmers used MOC. It is a multi-categorical variable that ranges from 0 to 5 since five production phases (e.g., plowing, seedling, planting, spraying, and harvest) are considered in this study.

To ensure that the treatment effect model is identifiable, the rural industry is considered the instrumental variable. The rural industries in the sample villages include agricultural businesses and other industries, such as the processing industry and rural tourism. These industries provide farmers with off-farm employment. This increases the opportunity cost of rice production for farmer households and may trigger farmers to quit farming (Qiu and Luo, 2021). Consequently, it could influence farmers' willingness to participate in MOC during rice production. Meanwhile, rural industries generally have no significant impact on the technical efficiency of rice farms. The regression results show that rural industry significantly affects farmers' participation decisions in MOC at the 5% level (Coefficient $= -0.858^{**}$, Prob $>$ chi square $= 0.002$) but has no significant effect on the technical efficiency of rice farmers (Coefficient $= -0.003$, Prob $>$ chi square $= 0.000$). It indicates that the selected instrumental variable is valid in this study.

We also used the socioeconomic characteristics of farmer households as the control variables. Specifically, we included individual characteristics of household heads (e.g., gender, age, education, health condition, training, off-farm work, and risk preference) and household resources (e.g., family size, income level, subsidies, land slope, land fertility, farm size, and machinery).

2.2. Estimation strategies

2.2.1. The stochastic frontier analysis

As a critical indicator of production performance, technical efficiency and its determinants have been widely discussed. We usually refer to the ratio of observable output to the maximum realizable output given the actual inputs as technical efficiency (Hong et al., 2019; Lawin and Tamini, 2019). Therefore, the utilization efficiency of different MOCs can be reflected by technical efficiency directly (Zheng et al., 2021). The technical efficiency can appropriately reflect the extent to which each observation achieves the feasible production frontier under the given mix of inputs (Bonfiglio et al., 2020; DeLay et al., 2022). Previous studies have shown that either the non-parametric method (data envelope analysis, DEA) (Haq, 2017; Liu et al., 2021; Guth et al., 2022) or the parametric method (stochastic frontier analysis, SFA) can be used to measure technical efficiency (e.g., Sabasi et al., 2019; Zheng et al., 2021; Zhu et al., 2021). In contrast, the SFA model can reduce the deviation caused by random factors (e.g., natural disasters). It is also less sensitive to outliers than the DEA model. Therefore, we employed the SFA model to calculate the technical efficiency of rice farmers.

TABLE 2 Descriptive statistics of variables.

Variables	Definition and measurement	Mean (S.D.)
Dependent variable		
TE	Technical efficiency of rice production	0.855 (0.106)
Independent variables		
Participation decision	1 = if household has adopted MOC in any phase, 0 = otherwise	0.926 (0.262)
Participation intensity	Number of production phases where the household adopted MOC (0, 1, 2, 3, 4, 5)	2.223 (1.222)
Control variables		
Gender	1 = male, 0 = otherwise	0.828 (0.378)
Age	Age of household head in years	60.371 (9.906)
Education	Number of years of schooling	6.802 (3.645)
Health condition	Self-reported health condition (1 = incapacity of work, 2 = poor, 3 = medium, 4 = good, 5 = excellent)	3.918 (1.063)
Training	1 = if farmer has participated in any agricultural training, 0 = otherwise	0.338 (0.474)
Off-farm work	1 = if farmer participated in off-farm work, 0 = otherwise	0.326 (0.469)
Risk preference	Farmer's attitude toward risk (1 = prefer high-risk investment, 2 = prefer medium-risk investment, 3 = prefer less risk investment)	2.697 (0.568)
Family size	Number of laborers (at least 6 months at home in a year) in the family	3.457 (1.705)
Income level	1 = if farmer household has been registered as a low-income family by government, 0 = otherwise	0.080 (0.272)
Subsidies	1 = if household has received government subsidies, 0 = otherwise	0.951 (0.217)
Land slope	1 = Level land, 0 = otherwise	0.923 (0.267)
Land fertility	1 = poor, 2 = medium, 3 = good	2.389 (0.619)
Farm size	Planting area of rice (mu)	22.975 (68.543)
Machinery	1 = if household owns agricultural machinery, 0 = otherwise	0.318 (0.466)
Instrument variable		
Rural industry	1 = if farmer's village has a rural industry, 0 = otherwise	0.169 (0.375)

There are two forms of functions widely used in the SFA model. One is the Cobb-Douglas production function, which requires fewer parameters. But this is subject to the assumption of a constant elasticity of substitution and follows a restriction on constant returns to scale consumption (Huan et al., 2022). Another is the Translog production function which can overcome the constraint of the above assumption. However, it may suffer from a potential multicollinearity problem. In this regard, following Shahbaz et al. (2022), the two production functions have been tested in this study, and the results of the log-likelihood ratio (LR) test show that the Translog production function is more appropriate.

Based on Ubabukoh and Imai (2022), the logarithm expression of the Translog production function is as follows:

$$\ln Y_i = \beta_0 + \beta_1 \ln K_i + \beta_2 \ln L_i + \beta_3 \ln A_i + \beta_4 \ln T_i + \beta_5 (\ln K_i)^2 + \beta_6 (\ln L_i)^2 + \beta_7 (\ln A_i)^2 + \beta_8 (\ln T_i)^2 + \beta_9 \ln(K_i L_i) + \beta_{10} \ln (K_i A_i) + \beta_{11} \ln(K_i T_i) + \beta_{12} \ln(L_i A_i) + \beta_{13} \ln(L_i T_i) + \beta_{14} \ln (A_i T_i) + (v_i - u_i) \tag{1}$$

Where ln denotes the natural logarithm; the subscript i denotes the i-th rice farmer; β_i is the parameter to be estimated for the input variables and their interaction terms; Y is the output indicator in this study, and it represents the total rice yield of farmer i; K, L, A, and T are all input indicators; K represents the farmer's capital input; L represents the farmer's labor input; A represents the farmer's land input; T represents the machinery cost; v_i is a random error; u_i is an inefficiency term; and $u_i \sim ii\, dN^{+}(\mu, \sigma_u^2)$.

The households' technical efficiency is measured following Lawin and Tamini (2019), given as follows:

$$TE = \frac{E(Y_i|U_i, Q_i)}{E(Y_i|U_i = 0, Q_i)} = \exp(-U_i) \tag{2}$$

Where TE is the technical efficiency of farmer households, Q_i represents the total input of rice production, $E(\,Y_i|\,U_i, Q_i)$ represents the expected value of actual output, and $E(\,Y_i|\,U_i = 0, Q_i)$ denotes the expected value of the output on the frontier when the technical inefficiency term u_i equals zero.

2.2.2. The treatment effect model for estimating the impact of farmers' MOC on production performance

Farmers' participation decisions in MOC usually depend on observable characteristics (e.g., age, gender, education level, family size, farm size, and health condition) and unobservable characteristics (e.g., farmers' innate abilities). Their decisions usually do not follow the principle of random assignment and may cause self-selection bias among the sample farmers. It is not suitable to use ordinary least squares (OLS) for empirical estimation. Thus, some scholars have employed the propensity score matching

(PSM) method to alleviate the issue (e.g., Yang et al., 2020; Zhang et al., 2020). However, the PSM model can only address the self-selection bias introduced by observable variables. Accounting for both observed and unobserved variables (Cong and Drukker, 2000), this study uses TEM to eliminate the potential endogeneity problem and analyze the effect of MOC on the technical efficiency of farmers.

The estimation of TEM involves two stages. The first stage is referred to as a selection equation. It describes the farmers' participation decision in MOC in rice production. Following the principle of random utility maximization, a farmer adopts the MOC if the random utility obtained through the MOC is greater than that of the farmers' non-participation in MOC. Thus, the discrete selection model can be specified as follows (Ma and Abdulai, 2017):

$$M_i^* = \gamma z_i + \varepsilon_i, M_i = \begin{cases} 1, if\ M_i^* > 0 \\ 0, if\ M_i^* \leq 0 \end{cases} \tag{3}$$

Where M_i^* is the latent variable and M_i is its proxy. If M_i^* is >zero, it means the farmer i participated in MOC, and the M_i value is 1. Otherwise, M_i equals 0. z_i denotes the vector of explanatory variables, and it includes farmers' socioeconomic characteristics that may influence farmers' participation decisions in MOC. γ is a parameter to be estimated. ε_i is a random error term.

The second stage is referred to as an outcome equation. It can be specified as follows:

$$T_i = \alpha X_i + \delta M_i + \varphi_i \tag{4}$$

Where the dependent variable T_i refers to the technical efficiency of rice farmers, α and δ are parameters to be estimated, and φ_i is a random error term. X_i is a vector of control variables that are expected to influence technical efficiency.

Based on Equations (3) and (4), we can figure out the association between MOC and technical efficiency. Further, the average treatment effect (ATE) can be used to accurately calculate the difference in technical efficiency between participants and non-participants in MOC. The formula is given as follows:

$$ATE = E(T_i|M_i = 1) - E(T_i|M_i = 0) \tag{5}$$

Where $E(T_i)$ represents the expected technical efficiency of the two groups.

2.2.3. The multivalued treatment effect model for exploring the effect of farmers' participation intensity of MOC on production performance

We used the multivalued treatment effect (MTE) model to estimate the average treatment effects of farmers' different participation intensities in MOC on the technical efficiency of their rice farms. Following Ma et al. (2021), the random vector $Z_i = (Y_i, T_i, X_i)$ can be observed for each sample farmer household i (i = *1, 2, …, N*). Y_i denotes a vector of the outcome variable technical efficiency, T_i represents a multivalued treatment variable of the farmers' participation intensity, and X_i is a vector of a farmer's socio-economic characteristics. D_{it} (T_i) denotes that farmer i received the treatment t, and it can be defined (Ma and Abdulai, 2017) as follows:

$$D_{it}(T_i) = \begin{cases} 1, if\ T_i = t \\ 0, otherwise \end{cases} \tag{6}$$

In particular, the outcome variable Y_{it} contains a set of potential outcomes (Y_{i1}, …, Y_{it}, …, Y_{iJ}). But only one outcome Y_i can be realized by an individual farmer's household in each period. Following Issahaku and Abdulai (2020), Y_i can be expressed as follows:

$$Y_i = \sum_{t=0}^{J} D_{it}(T_i) Y_{it} \tag{7}$$

Given that the difference between two potential outcomes is the treatment effect (τ), the treatment effect between two distinct treatment levels (m and k) can be expressed as follows:

$$\tau = E\left[Y_{im} - Y_{in}\right], \forall m, n \in J \tag{8}$$

Given the fact that rice farmers can only choose the intensity of participation in MOC during each complete rice production cycle, only Y_{im} or Y_{in} can be observed for an individual farmer's household i. Thus, we cannot identify the treatment effect defined in Equation (8) without further assumptions (Ma et al., 2018; Issahaku and Abdulai, 2020). To eliminate the non-randomness of participation intensity, the MTE model is established on the basis of two assumptions, namely, the conditional independence assumption (CIA) and the overlap assumption (Cattaneo, 2010; Ma et al., 2018).

We controlled for observable pretreatment characteristics as much as possible to meet the CIA assumption. It implies that the farmer's choice of participation intensity can be regarded as a random assignment (Issahaku and Abdulai, 2020). The overlap assumption can be tested by the density plots of the generalized propensity scores (GPS) estimated from the multinomial Logit model (Cattaneo et al., 2013). It ensures that each covariate X_i has a positive probability and satisfies the following conditions:

$$0 < \Pr\left[T_i = t | X_i = x\right] \tag{9}$$

Based on the above assumptions, we can guarantee the independence of each farmer at t level from other individuals and calculate the conditional expected potential outcome for each participation intensity. Thus, the conditional expectations under the participation intensities m and n can be specified (Ma et al., 2021) as follows:

$$E\left[Y_{im}|X_i\right] = E\left[Y_i|T_i = m, X_i\right] = \beta_{0m} + X_m' \beta_{1m} \tag{10}$$

$$E\left[Y_{in}|X_i\right] = E\left[Y_i|T_i = n, X_i\right] = \beta_{0n} + X_n' \beta_{1n} \tag{11}$$

Then, the augmented inverse probability weighting (AIPW) estimator is used to calculate the average treatment effects, and an inverse probability weighted regression adjustment (IPWRA) estimator is used to check the robustness of the results. The two estimators are doubly robust (Linden et al., 2016), and the average treatment effect can be estimated as follows:

$$ATE_{mn} = \frac{1}{U}(E[Y_{im}|X_i] - E[Y_{in}|X_i]) = \frac{1}{U}\left[\sum_{i=1}^{U}(\beta_{0m} - \beta_{0n}) + \sum_{i=1}^{U} X_i'(\beta_{1m} - \beta_{1n})\right] = (\beta_{0m} - \beta_{0n}) + \frac{1}{U}\sum_{i=1}^{U} X_i'(\beta_{1m} - \beta_{1n}) \quad (12)$$

Where U refers to the number of samples with the treatment $T_i = m$ and $T_i = n$. β_{0i} and β_{1i} are vectors of parameters.

3. Results and discussion

3.1. The production performance of rice farmers

In this study, the technical efficiency of rice farmers is estimated only for one period, so the production function contains no time variable t. In this regard, an LR test statistic is required, and it consists of two steps. The first step is to test the applicability of the SFA model (Liu et al., 2020), and the null hypothesis is $H_0: \gamma = 0$. If the null hypothesis is rejected by the test results, it indicates that the SFA model is more applicable than the DEA model. The second step is to verify which production function form is better suited to the model. The null hypothesis of the Cobb–Douglas function (H_0) is that the coefficients of the input variables and their interaction terms are zero. The alternative hypothesis (H_1) represents the Translog function. The more appropriate model can also be identified by comparing the results of the LR tests.

Based on the above hypothesis of the SFA model, the results contribute to revealing the applicability of the models and production function forms. In particular, the coefficient γ in Translog form is equal to 0.947 and is significant at the 1% level. Meanwhile, the result of the LR test is 149.175, which is greater than the critical value of the mixed chi-square distribution at the 1% level, $x^2_{1-0.01}(2) = 8.273$. These findings show that the first hypothesis $H_0: \gamma = 0$ is rejected, indicating that the SFA model is more suitable than the DEA model. In terms of the second LR test that cannot be directly observed, we calculated the result by log-likelihood. The log-likelihood in the Translog function is 168.447, and for the Cobb–Douglas function, it is 59.126. The result also rejects the second hypothesis, suggesting that the Translog function is more appropriate than the Cobb–Douglas function ($LR = -2 \times [\ln L(H_0) - \ln L(H_1)] = -2 \times [59.126 - 168.447] = 218.642 > \chi^2_{1-0.01}(2) = 8.273$).

Table 3 shows the estimated technical efficiency of rice farmers based on the Translog function. The technical efficiency of overall samples ranges from 0.273 to 0.979. The average technical efficiency of MOC participants and non-participants is 0.855 and 0.846, respectively, indicating that MOC may play a positive role in improving technical efficiency. The minimum score of technical efficiency among MOC participants (0.273) is not as high as that of non-participants (0.437). It may be attributed to the negative effect of the overuse of MOC in agricultural production by small-scale farmers. Technical efficiency may be decreased by the excessive inputs of MOC in small farms in developing regions. However, the potential heterogeneous effect of MOC on technical efficiency needs to be explored in later sections.

TABLE 3 Description of rice farmer's technical efficiency.

	Mean	Std. dev.	Min	Max	Observations
Participants	0.855	0.105	0.273	0.979	602
Non-participants	0.846	0.121	0.437	0.955	48
All	0.855	0.106	0.273	0.979	650

TABLE 4 Estimation results of the treatment effect model.

Variable	Selection equation	Outcome equation
Gender	−0.325 (0.227)	0.032*** (0.012)
Age	−0.010 (0.009)	0.000 (0.000)
Education	−0.003 (0.022)	0.002* (0.001)
Health condition	−0.168** (0.075)	0.002 (0.004)
Training	−0.056 (0.154)	0.011 (0.010)
Off-farm work	0.365** (0.181)	−0.014 (0.010)
Risk preference	0.037 (0.123)	−0.006 (0.008)
Family size	0.048 (0.044)	−0.007*** (0.003)
Low-income households	0.011 (0.273)	−0.023 (0.016)
Subsidies	−0.630 (0.492)	−0.003 (0.020)
Land slope	−0.251 (0.300)	0.022 (0.016)
Land fertility	−0.050 (0.117)	0.021*** (0.007)
Farm size	−0.002* (0.001)	0.000* (0.000)
Farm machinery	−0.259 (0.159)	0.022** (0.010)
Rural industry	−0.435*** (0.147)	–
MOC	–	0.182*** (0.017)
Constant	3.724*** (0.991)	0.586*** (0.055)
ath (ρ)	–	−1.041*** (0.110)
ln (σ)	–	−2.209*** (0.031)
Wald chi^2	–	157.210***
Log-likelihood	–	418.992
LR test of indep. eqns.	–	24.55***
Observations	650	650

The standard deviation is given in parentheses.
***Indicates $p < 0.01$; **indicates $p < 0.05$; *indicates $p < 0.10$.

3.2. Determinants of farmers' participation in MOC

The results in Table 4 show that the coefficient of residual correlation ath (ρ) is significant with a negative sign, suggesting that the selection bias caused by observable and unobservable factors exists in the sample (Manda et al., 2016; Ma and Abdulai, 2017). The effect of MOC on technical efficiency would be underestimated if the selection bias was not considered. The result of the Wald test also significantly rejects the null hypothesis that the MOC is exogenous (Ma et al., 2018). Therefore, TEM is appropriate to present a more solid estimation of the effect of MOC on the technical efficiency of rice farmers.

The determinants of MOC estimated by the selection equation are listed in the second column of Table 4. The coefficient of farmers' health condition is significant with a negative sign, suggesting that farmers with better health conditions have less participation in MOC. Farmer's poor health conditions would worsen farm labor shortage for agricultural production, and MOC can be adopted as an alternative solution. Similarly, off-farm work also has a significant positive effect on farmers' MOC, indicating that families with off-farm employment are more likely to participate in MOC. This finding is consistent with that of Zheng H. et al. (2022). The income obtained from off-farm work can enable farmers to purchase more services in agriculture. Farm size shows a significant negative impact on farmers adopting MOC. Farmers with larger farms have a lower probability of participating in MOC. The possible explanation is that these farmers are more likely to purchase agricultural machinery and hire long-term laborers rather than adopt MOC (Qiu and Luo, 2021). The coefficient of the rural industry is significant and negative at the 1% level, and the instrument variable is valid.

3.3. The impact of MOC on production performance

The third column of Table 4 presents the influence of factors on the technical efficiency of rice farmers. The results show that MOC has a statistically significant and positive impact on farmers' technical efficiency. It indicates that the adoption of MOC can enable farmers to achieve higher technical efficiency in rice production. The development of agricultural markets can realize the effective allocation of economic resources (e.g., labor and agricultural machinery), especially for small-scale farmers with a shortage of agricultural resources in developing countries.

Regarding the farmers' individual characteristics, gender and education exert a statistically significant and positive influence on technical efficiency. The coefficient of the gender variable implies that male-headed farmers are better at improving technical efficiency than female-headed farmers. Danso-Abbeam et al. (2020) also revealed the impact of gender on technical efficiency in Ghanaian cocoa farms. They attributed these efficiency variances to differences in farmers' resource endowments. The coefficient of the education variable suggests that higher education levels have a positive impact on farmers' technical efficiency. Existing studies have shown that better education can help farmers learn new technologies and exchange information (Ruzzante et al., 2021; Zhu et al., 2021).

With respect to household characteristics, the variable of family size exerts a negative and statistically significant impact on technical efficiency. This finding is in line with Zheng et al. (2021), who attributed this correlation to family composition. The quantity of the labor force is not equal to the size of the family, which may include many non-workers such as the elderly or children.

TABLE 5 Average treatment effects of MOC on technical efficiency.

	Participant	Non-participant	ATE	Percentage
Technical efficiency	0.852 (0.001)	0.846 (0.001)	0.006*** (0.001)	0.709%

The standard deviation is given in parentheses.
***Indicates $p < 0.01$.

Land fertility, farm size, and farm machinery are statistically significant with a positive sign. First, land fertility can improve technical efficiency by increasing output per unit (Al-Amin et al., 2016). Second, a potential pathway for the impact of the land area could be the reduction of inputs and losses per unit area through large-scale production (Liu et al., 2019). Finally, the finding of the land machinery variable is consistent with Shi et al. (2021), who verified that purchasing agricultural machinery is good for the technical efficiency of agricultural production.

3.4. Average treatment effect of MOC

We calculated the average treatment effect (ATE) of MOC based on the estimated results of the selection equation and outcome equation. The ATE represents the difference in technical efficiency between farmers with and without MOC in rice production. The results of ATE are presented in Table 5. The statistically positive and significant coefficient of ATE indicates that farmers' participation in MOC can increase the technical efficiency of their farms. Thus, purchasing production services through the agricultural market is effective to improve the food production performances of small-scale farmers in developing countries (Qiu and Luo, 2021; Chen T. et al., 2022).

Table 6 presents the results of the treatment effects of participation intensity on technical efficiency estimated by the AIPW estimator. For a straightforward interpretation of the coefficient estimates, we also calculated the percentage of change in ATE (Ma et al., 2021).

The results indicate that the adoption of MOC with intensities ranging from 1 to 5 can significantly increase farmers' technical efficiency compared with non-participants. Interestingly, the effect of MOC on technical efficiency does not increase continuously as farmers' participation intensity increases but shows a downward trend after rising initially. In other words, farmers' participation intensity in MOC on technical efficiency presents an inverted U-shaped effect. Technical efficiency peaks when the participation intensity in MOC is 3, indicating farmers who adopt MOC in three production phases have optimal technical efficiency on their farms. However, the declining trend in the effect of MOC on technical efficiency after the peak is much weaker than the upward trend before it. In other words, although the technical efficiency of farmers whose participation intensity is greater than three production phases decreases, it is still higher than that of farmers who adopt MOC only in one or two phases.

The possible insights can be explored with respect to this finding. First, farmers need to adhere to participation in MOC because the results confirm the substantial benefits of technical efficiency associated with MOC. Second, it is necessary for farmers to consider

TABLE 6 ATE results (AIPW estimator).

From 0 to n	ATE estimates		Percentage change in ATE	
	Coefficients	*z*-value	Coefficients	*z*-value
From 0 to 1	0.035** (0.017)	2.14	0.044** (0.021)	2.09
From 0 to 2	0.042*** (0.014)	3.10	0.052*** (0.017)	2.98
From 0 to 3	0.056*** (0.013)	4.18	0.069*** (0.017)	3.97
From 0 to 4	0.051*** (0.015)	3.40	0.063*** (0.019)	3.27
From 0 to 5	0.047*** (0.015)	3.11	0.058*** (0.019)	3.01

The standard deviation is given in parentheses.
***Indicates $p < 0.01$; **indicates $p < 0.05$.

TABLE 7 ATE results (IPWRA estimator).

From 0 to n	ATE estimates		Percentage change in ATE	
	Coefficients	*z*-value	Coefficients	*z*-value
From 0 to 1	0.036** (0.016)	2.27	0.044** (0.020)	2.23
From 0 to 2	0.044*** (0.013)	3.46	0.054*** (0.016)	3.33
From 0 to 3	0.057*** (0.012)	4.66	0.071*** (0.016)	4.42
From 0 to 4	0.055*** (0.014)	3.91	0.067*** (0.018)	3.75
From 0 to 5	0.049*** (0.013)	3.86	0.061*** (0.016)	3.70

The standard deviation is given in parentheses. ***Indicates $p < 0.01$; **indicates $p < 0.05$.

the appropriate participation intensity of MOC in their practices. Excessive costs invested in a small-scale farm may result in allocative inefficiency and diseconomies of scale (Shi et al., 2021), particularly in developing regions.

3.5. Robustness check of the impact of MOC intensity on production performance

Table 7 presents the results of the IPWRA estimator. It shows that farmers who move from 0 to n participation intensity in MOC have positive associations with ATE. The ATE peaked at degree 3 and presents an inverted U-shaped effect. The percentage of change in ATE is similar to the results presented in Table 5. Hence, the estimated results of the previous model are robust. There are no biased estimates caused by the misspecified model (Linden et al., 2016; Ma and Abdulai, 2017).

4. Heterogeneous effects in production phases

To better understand the inverted U-shaped effect of participation intensity in MOC on technical efficiency, this study attempts to explain it from two perspectives: the attributes of different production phases and the resource endowment of farmer households.

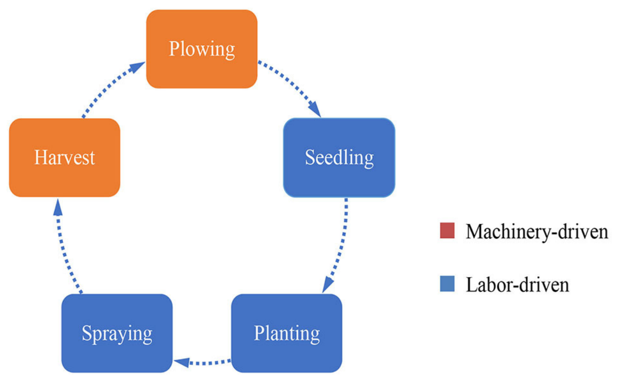

FIGURE 1
The classification of production phases.

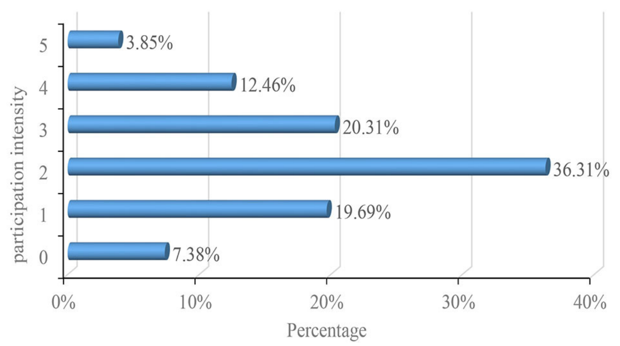

FIGURE 2
Percentage of farmers with different participation intensities of MOC.

It has been noted that farmers' decisions about purchasing services are deeply influenced by the type of each production phase. As highlighted in previous studies (Qiu and Luo, 2021; Qian et al., 2022) the production phases can be divided into "labor-intensive," "capital-intensive," and "technology-intensive" according to their attributes. For simplification, we classified the production phases into "machinery-driven" and "labor-driven" phases based on the difference in demand for labor or machinery in each phase. Figure 1 shows the categories of the five production phases.

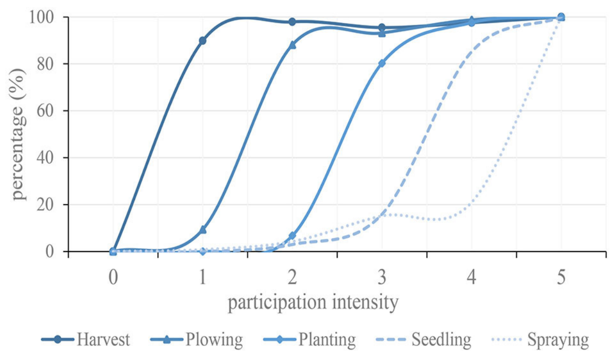

FIGURE 3
The percentage of MOC of each phase at different degrees.

Specifically, plowing and harvesting are classified as machinery-driven phases, while seedling, planting, and spraying can be seen as labor-driven phases.

We presented two figures for analyzing the heterogeneous effects. Figure 2 shows the percentages of farmers with different participation intensities in MOC. The percentages of MOC in each phase at different participation intensities are given in Figure 3.

As presented in Tables 6, 7, the value of ATE continued to increase in participation intensity from 0 to 1 and then to 2. This process of changing the intensity of MOC covered nearly 56% of the sample farmers in Figure 2. Meanwhile, corresponding to intensity 2 in Figure 3, 97.9% of farmers in this period adopted MOC for harvesting, and 88.1% of farmers purchased plowing services through the market. The descriptive statistics imply that rice farmers preferred MOC in machinery-driven phases.

The possible explanations can be put forward in this study. First, in terms of production phases, the harvesting and plowing services of the market are characterized by higher mechanization and lower supervision costs (Qing et al., 2019; Qian et al., 2022). Purchasing machinery services can contribute to improving technical efficiency by reducing labor input (Wang et al., 2020). Second, from the perspective of resource endowment of farmer households, MOC is much less expensive than purchasing agricultural machinery and learning how to use it for farmers. Table 8 presents that the proportion of self-owned machinery ranges from 3.846 to 28.462%. The low percentage implies that the majority of farmers have to rely on alternative solutions (e.g., purchasing machinery services or investing more labor effort) in the production phases. The estimation of mean difference analysis also shows that farmers who have purchased agricultural machinery are farmers with larger farms (Qian et al., 2022). Hence, the adoption of MOC in machinery-driven phases can be an economic choice, especially for small-scale farmers who usually cannot afford the machinery.

As shown in Figure 3, the proportion of MOC in the planting phase has increased from 6.780% with intensity 2 to 80.303% with intensity 3. According to the prior results, the technical efficiency is highest when farmers adopt MOC in three production phases. Thus, the MOC in planting plays a crucial role in farmers' improvement of technical efficiency.

Rice farmers prefer MOC in the harvesting and plowing stages than in the planting stage, which is usually labor-driven in rural China. Labor shortage appears in the planting phase of rice production. The increasing labor costs in rural China and the difficulty in the supervision of pure labor efforts may account for this (Wang et al., 2016). In the same sense, the MOC was introduced later by farmers in labor-driven phases than in machinery-driven phases. However, the role of MOC in increasing technical efficiency cannot be ignored. The increase in technical efficiency in the process of planting can be attributed to three aspects. First, this finding suggests that the marginal effect of labor costs on technical efficiency has not yet exceeded that of the output created by purchased services. Second, the planting service can compensate for the constraint of a labor crunch on agricultural production. Under the high seasonal requirements of the planting phase, the planting service can help farmers complete the work in a short period and mitigate the impact of extreme weather on agriculture (Javed et al., 2020; Ogunleye et al., 2021). Third, the specialized planting team in rural areas enables farmers to avoid frequent searches for individual employees and save transaction costs (e.g., information costs), thus improving the technical efficiency of food production.

Figure 3 also displays the trend of adoption of MOC in the seedling and spraying phases. As labor-driven phases, they present an obviously low rate of MOC until the participation intensity reaches 4. According to the prior results, when farmers used MOC in these phases, the technical efficiency showed a declining trend. The possible reasons are as follows: First, the seedling and spraying services lead to higher supervision costs. The coefficient of the spraying phase in Table 9 is negative, suggesting that the adoption of MOC in the spraying phase would decrease the technical efficiency of rice farmers. Second, among households with 4 or 5 intensities, the input of family labor in agriculture is relatively small. In these farmer households, agriculture may not be the primary source of income. Family members can be engaged in off-farm work when they have adopted MOC in full production phases. The management of their farms becomes more extensive, thus reducing technical efficiency (Xu et al., 2019).

5. Conclusions and policy implications

The MOC is beneficial for small-scale farmers to overcome resource constraints and promote sustainable food production in developing countries. The shortage of agricultural resources in these areas may encourage farmers to develop market transactions. We attempted to assess the impact of MOC on the production performance of rice farmers in China, using the treatment effect model and multivalued treatment effect model based on the 2020 CLES database.

There are three main findings that can be drawn from this study: First, the MOC imposes a positive effect on the technical efficiency of small-scale farms in developing countries such as China. Farmers' participation in MOC can increase the technical efficiency of small-scale farms by 0.709%. Second, the relationship between the intensity of MOC and technical efficiency resembles an inverted U-shaped effect rather than a simple linear relationship. Specifically, when farmers' participation intensity does not exceed critical point 3, technical efficiency increases as the intensity does. Otherwise, technical efficiency decreases if the intensity increases after the critical point. The downward trend in technical efficiency after the peak is considerably weaker than the upward trend before it. Third, the MOC

TABLE 8 Use of agricultural machinery.

	Harvester	Cultivator	Transplanter	Tractor	Truck
Percentage	5.692%	12.769%	5.692%	28.462%	3.846%
Mean (Yes)	140.946	101.456	166.676	55.092	211.888
Mean (No)	17.145	10.349	14.444	8.756	15.679
Difference	123.801***	91.107***	152.231***	46.335***	196.209***

The farm size of small-scale farmers is <50 mu (1 mu = 1/15 ha).
***Indicates $p < 0.01$.

TABLE 9 Impacts of MOC on technical efficiency (each production phase).

	TE (tobit model)				
	Coefficient	Std. err.	Prob > chi^2	Log-likelihood	Control variables
Harvest	0.025*	0.013	0.000	560.460	Added
Plowing	0.005	0.010	0.000	558.777	Added
Planting	0.018**	0.009	0.000	560.957	Added
Seedling	0.012	0.010	0.000	559.342	Added
Spraying	−0.001	0.013	0.000	558.667	Added

**Indicates $p < 0.05$; *indicates $p < 0.10$.

among farmers has a heterogeneous effect in different production phases. Most farmers prefer MOC in machinery-driven phases, which are easier to supervise, than labor-driven phases such as planting. There are distinct impacts of MOC in different production phases on the technical efficiency of small-scale farms. Specifically, the adoption of MOC in harvesting, plowing, or planting has a positive effect on the technical efficiency of their farms, while the adoption of MOC in seedling and spraying presents a negative effect on the technical efficiency of their farms.

Several implications can be considered based on the findings of this study. First, policymakers are suggested to employ various channels to enhance the organization of smallholders, in order to stimulate farmers' willingness to participate in MOC. The high cost may decrease farmers' adoption of MOC. Through rural cooperatives or farmers' social networks, the government can organize farmers to participate intensively in MOC. It can help to reduce production cooperation costs, attract participants to provide production services and achieve the sustainable development of food production. Second, policymakers and stakeholders may take care of the negative effect of MOC on the production performance of small-scale farms. Excessive participation in the MOC of small-scale farmers may reduce technical efficiency in agricultural production. Thus, it affects the sustainability of food production. However, the government can promote land transfer among these farmers, achieve large-scale operation of land resources, and improve the effect of MOC through economies of scale. Third, policymakers can enhance machinery subsidies to promote MOC in machinery-driven production phases, since the use of machinery reduces supervision costs in agriculture. It can guarantee the sustainability of farmers' consumption by reducing their production inputs. In the same sense, the investment in R&D of machinery that is applicable for small-scale farms can be supported, in order to transform the existing labor-based MOCs with advanced machinery.

This study detected the impact of farmers' MOC on their food production performance. However, there are still limitations. First, this study examined the case of rice farmers in China's Jiangsu Province. The findings should be prudently extended to other crops and other regions with different resource endowments. Second, the cross-sectional data employed in this study only focus on the short-term effects of MOC on agricultural production performance. Further studies should be conducted with a panel dataset and investigate the impact of farmers' MOC in multiple factor markets on sustainable agricultural production.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

CZ contributed to the conceptualization, methodology, investigation, data curation, formal analysis, and writing—original draft. YZ contributed to the conceptualization, investigation, formal analysis, project administration, funding acquisition, and writing—review and editing. All authors contributed to the manuscript revision and read and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

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