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Efficiency of agricultural cooperative members in Indonesia

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ABSTRACT

The food supply's stability is dependent on agricultural productivity, which, in turn, depends on the efficient allocation of production factors. This research analyzes the efficiency levels of rice farmers and compares them between cooperative members and non-members. This study quantifies efficiency using the stochastic frontier analysis (SFA) method and compares the results using the propensity score matching (PSM) method, which addresses potential selectivity bias resulting from the decision to join a cooperative. The study utilizes cross-sectional data from the Badan Pusat Statistik (BPS) of the Republic of Indonesia, encompassing a sample size of 68,204 farmers. The analysis reveals that the majority of farmers operate within an efficiency range of 70-90 percent. Cooperative members exhibit higher efficiency levels than non-members, with a 2.1 percent increase during the wet season and a 3.1 percent increase during the dry season. Researchers employ an alternative method, coarsened exact matching (CEM), to ensure robustness, yielding results similar to the PSM model. This research provides evidence that cooperatives have the potential to significantly enhance agricultural efficiency. The findings underscore the importance of developing and supporting cooperatives to enhance the overall welfare of farmers.

Contribution/ Originality: This study provides rigorous insights into the role of cooperatives in Indonesia, contributing to our understanding of how the cooperative movement impacts the well-being of its members. Additionally, the paper provides a comprehensive analysis of the efficiency of rice farmers in Indonesia. This study is unique as it utilizes the 2013 Agricultural Census from the Badan Pusat Statistik (BPS) of the Republic of Indonesia, along with an impact evaluation method that has not been previously used by other researchers.

1. INTRODUCTION

The agricultural sector is a crucial component in economic development, particularly for Indonesia, an agricultural nation. A stable domestic food supply, supported by robust agricultural production, is vital for strengthening food security. Addressing food issues should take precedence before restructuring other sectors. In developing countries, the agricultural sector significantly contributes to gross domestic product (GDP), although there is a tendency for this figure to decrease with ongoing structural transformation. The Indonesian government's initiative to improve the agricultural sector is highly appropriate (Martin, 2019; Timmer, 2002). In 2021, the agricultural sector in Indonesia contributed approximately 13 percent to the GDP, ranking second. Its share exceeds

25 percent, including the agriculture-based agro-industry (Badan Pusat Statistik, 2023).

The government aims to enhance productivity, as reflected in the increased crop yields. Previous research, however, indicates that productivity results not only from increased crop yields but also from efficient allocation of production factors. The efficiency level determines farmers' profits, incentivizing them to become cooperative members (Boediono, 1982). Efficiency is paramount in economics, especially when resources are scarce and the adoption of new technology is slow. Improved efficiency allows for increased productivity without additional resources or the adoption of new technology (Adeyemi, Okoruwa, & Ikudaisi, 2017; Furuya & Futakuchi, 2006).

Efficiency analysis is typically associated with farmers' ability to achieve optimal output levels using specific resources at the lowest possible cost (Bibi, Khan, & Haq, 2021; Danso-Abbeam, Fosu, & Ogundeji, 2021; Ramukhithi et al., 2023). Efficiency is the relative performance of the processes that transform inputs into outputs. Agriculture is considered efficient when it produces a specific output with minimal or maximum output from a given set of inputs (Cornwell & Schmidt, 2008). A production process is efficient if its output lies on the production frontier. Outputs below the production frontier are deemed inefficient (Coelli, Rao, O'Donnel, & Battese, 2005).

The evaluation of efficiency commonly employs two methodologies. The initial methodology encompasses non-parametric strategies, notably exemplified by the data envelopment analysis (DEA) method. In contrast, the second methodology pertains to parametric approaches, typified by stochastic frontier analysis (SFA). The DEA method, characterized by its absence of a fixed functional form, is susceptible to specification errors (Cornwell & Schmidt, 2008). Conversely, SFA, sensitive to functional form selection, systematically incorporates random errors and attributes any deviations from the frontier to stochastic effects and inefficiency. This research utilizes the SFA approach to assess efficiency, building on the methodologies employed by Onuwa, Folorunsho, Binuyo, Emefiene, and Ifenkwe (2021) in their study of sweet potato farmers in Nigeria and Ma, Renwick, Yuan, and Ratna (2018) in examining apple farmers in China.

Low production and transaction costs contribute to high agricultural efficiency. By collaborating, farmers can reduce production costs, as collective purchases in large quantities lead to lower prices. This aligns with organizational theories such as contract or transaction theory, which posit that uncertainty, risk, and asymmetric information increase transaction costs, potentially causing market inefficiencies and even market failures. Through cooperation or organization, economic activities become more efficient (Williamson, 2002, 2010).

The development of cooperatives in Indonesia presents a significant challenge, despite the fact that constitution states that the national economy must be based on economic democracy with principles of cooperation. Cooperatives are the most suitable form of enterprise in line with the constitutional mandate, serving to improve the living standard for people in developing countries (Hatta, 1957). The concept of cooperatives aligns with the directives of sustainable development goals (SDGs), a global movement to combat poverty and hunger while promoting community well-being. Cooperatives play a crucial role in achieving these goals by fostering economic cooperation, reducing inequalities, and improving people's livelihoods, particularly in rural and underserved areas (United Nations Development Programme, 2022).

Indonesia has 127,856 active cooperatives, 27,100,372 members, and total assets worth Rp. 251 trillion. The majority of these cooperatives are located in Java (Ministry of Cooperatives and SMEs of the Republic of Indonesia, 2022). Table 1 shows that Indonesian cooperatives' turnover was only 1.1 percent of GDP, whereas their business surplus to GDP was only 0.05 percent in 2020. This discrepancy poses a future challenge: How can cooperatives be on par with corporations and become one of the pillars of the Indonesian economy? The development of cooperatives will progress rapidly if their members experience significant benefits, whether in terms of increased productivity or business efficiency.

Table 1. Cooperative statistics in Indonesia, 2000-2020.

Criteria	2000	2005	2010	2020
Number of cooperatives (Unit)	103,077	134,963	177,482	188,181
Active cooperatives	88,930	94,818	124,855	127,124
Members (Million people)	27.3	27.3	30.5	25.1
Annual member meeting (Unit)	36,283	45,508	55,818	47,115
Business volume (Billion rupiah)	23,122.2	40,831.7	76,822.1	174,033
Business surplus (Billion rupiah)	694.5	2,198.3	5,622.2	7,225.1
Ratio				
Members/Active cooperatives	307.0	287.9	244.3	197.4
Annual member meeting/Active cooperatives	40.8	48.0	44.7	37.1
Business volume/Active cooperatives (Million rupiah)	260.0	430.6	615.3	1,369.0
Business surplus/Active cooperatives (Million rupiah)	7.80951	23.1844	45.0298	56.8351
Business volume/GDP (Percent)	1.66	1.47	1.12	1.13
Business surplus/GDP (Percent)	0.05	0.08	0.08	0.05
GDP (Trillion rupiah)	1,389.8	2,785	6,864.1	15,434.2

Source: Ministry of Cooperatives and SMEs of the Republic of Indonesia (2022).

This research aims to elucidate how efficiency influences farmers' productivity and whether being a cooperative member contributes to more efficient production. The findings from this study are expected to provide insights into the role of cooperatives in Indonesia and contribute to understanding the impact of the cooperative movement on its members' well-being.

Numerous studies have explored the impact of cooperatives on the agricultural sector, yet the results remain uncertain, providing grounds for ongoing discussions. For instance, Ahn, Brada, and Méndez (2012) highlight the suboptimal efficiency of agricultural cooperatives in El Salvador. Other studies on apple cultivation in China find that farmers affiliated with cooperatives demonstrate superior levels of efficiency and productivity compared to those not associated with such entities (Ma & Abdulai, 2016; Ma et al., 2018). Research by Ito, Bao, and Su (2012) similarly points to a positive cooperative influence on watermelon farmers in China. However, the participation of farmers in cooperatives remains limited, particularly among those operating on a smaller scale.

This research endeavors to address this gap by assessing the impact of agricultural cooperative membership on the efficiency of farmer households in Indonesia. This study enriches existing knowledge by conducting empirical research using household-level data, which offers rigorous insights into the role of cooperatives in the agricultural sector. We employ impact evaluation methods to compare farmers' technical efficiency (TE), allowing us to assess the benefits of being cooperative members. Our analysis uses econometric methods capable of correcting for selectivity bias due to observable and unobservable factors. Specifically, we apply the propensity score matching (PSM) method, calculating propensity scores and matching samples to mitigate selectivity bias.

Another significant contribution to this research is its in-depth analysis of the efficiency of rice farmers in Indonesia. Given that rice is the second-largest agricultural product in Indonesia after palm oil (Food and Agriculture Organization, 2021), an analysis of the rice production sector is crucial for formulating strategies and policies.

The subsequent sections of this article are structured in the following manner: The following section conducts a literature review and formulates hypotheses. The third section provides an overview of the data sources and research methodology. The fourth section presents and discusses the research findings. The concluding section summarizes the study, explores the implications of our findings, addresses limitations, and offers suggestions for future research.

2. LITERATURE REVIEW

2.1. Farmers' Efficiency

Current research extensively discusses the efficiency of farmers using the stochastic frontier model, particularly focusing on farmers in Africa and Asia. In general, these farmers' performance efficiency is not yet optimal. Adeyemi et al. (2017) estimate the cost efficiency of rice millers in Southwest Nigeria using a normalized quadratic cost function model. They then connect the findings to the millers and their respective characteristics. The results indicate that the cost efficiency levels of rice millers are relatively low, ranging from 1 to 57 percent. Based on the study findings, they recommend, among others. Enhancing paddy production through research and extension services will increase production and decrease costs. Addressing the energy sector, the research revealed that using electric mills is more cost-effective than using diesel-operated mills.

Onuwa et al. (2021) analyzed the technical efficiency of sweet potato production in Nigeria. The variables used in the stochastic frontier model have a significant impact on sweet potato production's technical efficiency and output. This suggests that we can increase farm output in the study area by effectively utilizing resources in sweet potato production. Furthermore, the efficiency index of sweet potato farmers in the study area revealed that they are not operating at their optimal capacity.

Another study conducted in Ethiopia confirms that maize producers were operating with technical inefficiency. The study determined that the calculated technical inefficiency score was 69.03 percent. Consequently, this implies the possibility of increasing maize yield per hectare by 30.07 percent by utilizing the existing technology (Belete, 2020).

The Ugandan study employs a stochastic profit frontier model to calculate the profit efficiency of 442 rice farmers. The findings reveal that smallholder rice farmers face elevated seed and labor costs, leading to a suboptimal profit efficiency of approximately 59 percent, with variations observed in different locations and marketing models. Notably, farmers who engage in group marketing demonstrate higher levels of profit efficiency compared to their counterparts (Akite, Okello, Kasharu, & Mugonola, 2022).

The study in Ghana on the technical efficiency of cashew production, using the double bootstrap DEA method, reveals a mean efficiency of approximately 33 percent. Interestingly, the employment of a substantial amount of labor tends to diminish efficiency, whereas the use of insecticides and herbicides demonstrates the potential to enhance productivity (Danso-Abbeam et al., 2021).

In southern Italy, Benedetti, Branca, and Zucaro (2019) conducted a study to measure the input-specific technical efficiency of irrigated crop production and identify its determinants, with a particular focus on water usage. The results of the model demonstrate that the farms have similar levels of technical efficiency. The study confirms the literature by observing that organic farming in the area is less efficient than conventional farming, with the fertigation production system being more efficient. Furthermore, the model provides insights into the potential for increasing crop production efficiency by reorganizing the factors involved in the production process.

Bibi et al. (2021) conduct a study to assess the comparative analysis of technical and environmental efficiency in the agriculture sector of South Asia. Utilizing balanced panel data spanning from 2002 to 2016, the study encompasses six South Asian countries: Bangladesh, Bhutan, India, Nepal, Pakistan, and Sri Lanka. The findings indicate that, on average, South Asian countries have achieved a maximum level of technical efficiency, reaching 92 percent. The study suggests that by mitigating inefficiency effects within the current input and technology framework, agricultural production in the region could potentially increase by up to 8 percent

Khan et al. (2022) analyze the technical efficiency of rice-growing farmers in Pakistan. Estimates from the stochastic frontier model reveal that the mean technical efficiency in rice production is 87 percent, ranging from a minimum of 66 percent to a maximum of 99 percent. The study recommends that the local extension department arrange training programs for rice growers to develop their agronomic skills and provide them with technical knowledge for efficient resource allocation.

2.2. Cooperatives in the Agricultural Sector

Cooperatives are not merely profit-oriented entities; they also prioritize social benefits and the development of their surrounding communities (Launio & Sotelo, 2021; Mhembwe & Dube, 2017; Yu, Nilsson, Zhan, & Cheng, 2023). Cooperatives are associations of individuals who voluntarily join together in the economic, social, and cultural domains to fulfill common needs and aspirations through collectively owned and democratically operated businesses. Differing from nonprofit organizations, cooperatives aim to provide benefits to their members. Unlike corporations, which primarily seek profits, cooperatives commit to environmental and community improvement. In cooperatives, members contribute equally to decision-making, regardless of their ownership shares. Cooperatives should be competitive with other business forms, such as private or government-owned companies.

China has implemented policy initiatives supporting the professional farmer cooperative movement, leading to its growth and expansion (Deng, Huang, Xu, & Rozelle, 2010). Cooperatives significantly enhance farmers' incomes and improve their crop yields, profits, and overall earnings. They are also capable of raising the average TE. However, it is noteworthy that impoverished farmers may show less interest in joining as cooperative members (Ito et al., 2012; Ma & Abdulai, 2016; Ma et al., 2018).

A recent study in China employed empirical analysis of survey data collected from 466 rural households. The findings indicate that being a member of a cooperative has a positive impact on the subjective well-being of rural households. Additionally, income and social capital partially mediate the relationship between cooperative membership and subjective well-being. Consequently, to enhance subjective well-being, it is crucial to fully utilize the role of cooperatives in rural areas (Wu, Li, & Gao, 2022).

In the governments of developing countries in Africa, there is active support for rural producer organizations, such as cooperatives, to enhance the productivity of small-scale farmers. These rural cooperatives assist farmers in obtaining inputs and marketing their produce. In Ethiopia, for example, cooperatives have been instrumental in helping farmers increase their profits from crop sales. Membership in these cooperatives encourages the adoption of agricultural technology, which boosts farmers' productivity and well-being while also increasing their families' income and assets. However, other studies highlight the tendency of impoverished farmers to be less inclined to participate in these programs and sometimes excluded from decision-making studies (Abebaw & Haile, 2013; Bernard & Spielman, 2009; Mojo, Fischer, & Degefa, 2017).

In Ghana, cooperatives encourage members to participate in credit financing (Asante-Addo, Mockshell, Zeller, Siddig, & Egyir, 2017). In Nigeria, the impact of cooperatives on technology adoption, asset ownership, and poverty reduction has been positive (Wossen et al., 2017). Similar effects have been observed in the dairy sector in India, where cooperative members achieve profitability levels comparable to those of farmers working for multinational companies. Although the efficiency level of cooperative members is lower than that of global companies, it is higher than that of traditional farmers (Vandeplas, Minten, & Swinnen, 2013). Cooperative membership also increases milk yields, net profits, and compliance with local food safety standards (Kumar, Saroj, Joshi, & Takeshima, 2018).

In Nigeria, a study indicates that membership in an agricultural cooperative, in contrast to non-membership, presently exerts a positive influence on tomato yield for smallholder farmers in rural areas. These findings support the current contention that joining an agricultural cooperative can enhance the yield potential of tomato farmers (Akinola et al., 2023).

In Bosnia and Herzegovina, a study reveals the beneficial effects of cooperatives on enhancing farmers' working conditions and gaining access to markets. The findings suggest that fostering collective action among berry farmers can serve as an effective intervention for rural development, contributing to poverty alleviation and mitigating its adverse consequences (Gava, Ardakani, Delalić, Azzi, & Bartolini, 2021).

A recent investigation conducted in Indonesia confirms that being a member of a cooperative has a favorable and substantial effect on household income within the capture fisheries sector. Membership in a cooperative leads to an increase in household income, consequently enhancing overall living standards (Taniu, Sari, Satria, Haryanto, & Wardana, 2024).

2.3. Hypotheses

This study formulates two hypotheses: (H_1) the socioeconomic characteristics of households influence the decision to become cooperative members, and (H_2) cooperative membership positively impacts farmer efficiency.

3. DATA AND METHODOLOGY

3.1. Data

The Badan Pusat Statistik (BPS) of the Republic of Indonesia conducted the 2013 Agricultural Census, marking the sixth census since 1963. This census encompassed nine sub-sectors of household business activities: rice cultivation, food crops, horticulture, plantations, livestock, fish farming, fishing, forestry, and forested areas. It employed a two-stage sampling method. Initially, we selected several census blocks based on proportional probability. In the subsequent stage, households were chosen through systematic random sampling. Households qualified as samples if their harvest area was at least 1,700 square meters during the preceding year.

The government report stated that the census interviewed 123,652 households. The commodities examined included wetland rice (hybrid and non-hybrid) and upland fields. A significant majority (96.83 percent) of wetland rice households cultivated non-hybrid varieties, with only 3.17 percent growing hybrid rice. This study primarily focuses on non-hybrid agriculture, which most farmers practice during wet and dry seasons (Badan Pusat Statistik, 2014).

The census provided a detailed breakdown of the cost structure of rice farming for both wetland fields and upland areas. Its goals included gathering data on the cost structure of rice farming, including expenses for seeds, fertilizers, pesticides, labor, agricultural services, and other expenditures. Additionally, the census collected supporting data on challenges and business prospects, the condition of facilities and farmers' residential buildings, and household food security. The BPS conducted this census in all of Indonesia's cities.

Table 2. Sample criteria.

No.	Criteria	Quantity
1	Complete data ST2013 SPD	87,330
2	Farmers who did not engage in agricultural activities during the survey period	(407)
3	Data covering four planting seasons: two short dry seasons, one long dry season, and the wet season	(18,899)
Sample used		68,024

Note: The sample comprises both the extended dry season and the wet season, representing the seasons with the largest sample size. The data from the other two planting seasons were excluded from the dataset.

Source: Badan Pusat Statistik (2014).

Table 2 explains the sample criteria used in this study. The complete census dataset comprises 87,330 respondents. Of these, 407 respondents did not engage in agricultural activities during the survey period. This dataset captures four planting seasons in 2013–2014, including three dry and one wet season. We selected one dry and one wet season period, each with the largest sample size, for analysis. Samples related to the other periods were excluded from the dataset, reducing the total to 18,899 respondents. Consequently, the total sample used in this study consists of 68,024 respondents.

3.2. Stochastic Frontier Analysis

Farrel (1957) conceptualized efficiency as the capacity of a firm to generate the maximum possible output from a given set of inputs. This method entails calculating efficiency using observational data, focusing on a single output product, and considering multiple input factors. Adeyemi et al. (2017) highlighted that efficiency is a pivotal concept in economics, especially crucial for driving productivity growth in contexts where resources are limited and adopting new technology is gradual. Studying efficiency enhances productivity without necessarily increasing resource allocation or adopting new technology. Efficiency estimations can also illuminate whether farmers must augment their resources or technology to boost productivity. Generally, efficiency analysis pertains to the likelihood of agriculture producing the optimal output from a certain input level at the lowest possible cost. Efficiency is the relative performance of the process that transforms input into output (Onuwa et al., 2021).

Efficiency comprises three components: TE, allocative or price efficiency, and economic (cost) efficiency. A firm is technically efficient if it can produce the maximum output from a given set of inputs. An allocative or price-efficient firm, on the other hand, uses the optimal amount of inputs to produce an optimal output at a given price with the available technology. When a firm achieves both technical and allocative efficiency, it signifies its capacity to generate a specific output at the lowest cost, utilizing the available technology at that moment (Adeyemi et al., 2017; Farrel, 1957).

Researchers have developed two primary quantitative approaches to measure production efficiency: parametric SFA and non-parametric DEA. Data envelopment analysis does not presuppose a fixed functional form and does not consider noise in the data. Consequently, we calculate inefficiency based on all deviations from the efficiency frontier. In contrast, the SFA approach is parametric, sensitive to the choice of functional form, and accounts for random error. This approach attributes all deviations from the frontier to both random effects and inefficiency.

Aigner, Lovell, and Schmidt (1977) and Jondrow, Knox Lovell, Materov, and Schmidt (1982) developed the SFA model to estimate technical inefficiency, building upon the foundational research conducted by Farrel (1957). The stochastic frontier production function is particularly suited for measuring TE because it addresses shortcomings in the error term assumptions of conventional production functions. These conventional functions often face limitations in statistical inference regarding parameters and the resulting efficiency estimates. A notable advantage of the SFA model is its inclusion of stochastic random disturbances beyond farmers' control and the effects of inefficiency (Battese & Coelli, 1988). This model uniquely decomposes the error term into two parts: a random error that captures effects beyond the control of farmers, and an inefficiency component. As Coelli et al. (2005) describe, this model is a stochastic function because it acknowledges that stochastic (random) variables can limit output values.

The modeling and estimation of the stochastic frontier production function are crucial for understanding the relationship between output amounts and production inputs, factoring in the level of technology employed. SFA models are widely used in agricultural economics research, as evidenced by studies from Akite et al. (2022); Benedetti et al. (2019); Bibi et al. (2021), and González-Flores, Bravo-Ureta, Solís, and Winters (2014). Battese and Coelli (1995) initially proposed the stochastic frontier production model for panel data analysis, and maximum likelihood estimation (MLE) procedures typically estimate it. As Onuwa et al. (2021) demonstrate, the TE of a firm relates to the observed output (Y_i) in comparison to the corresponding frontier output (Y_i*), considering the available technology. This relationship is articulated in Equation 1 and 2.

$$TE_i = Y_i / Y_i^* \qquad (1)$$

$$TE_i = \frac{f(x_i;\beta)\ \exp(v_i - u_i)}{f(x_i;\beta)\ \exp(v_i) - \exp(-u_i)} \qquad (2)$$

Thus, $0 \leq TE_i \leq 1$

Therefore, technical inefficiency can be defined as 1 − TE. The general stochastic frontier production function for cross-sectional data in this study, based on the work of Jondrow et al. (1982) is represented in Equation 3:

$$Y_i = \beta_i X_i + V_i - U_i \qquad (3)$$

Here, Y_i signifies the output for the i-th sampled agricultural household. β_i is the vector of unknown parameters that need estimation, and X_i is the vector of explanatory variables for the i-th sample. V_i represents the independent and identically distributed random error, which follows a normal distribution with an unknown variance α^2. U_i is a non-negative random variable associated with technical inefficiency that cannot be observed. Thus, the observed output is below its potential output for a given technology and input level.

The technical inefficiency model employed in this study is the one developed by Battese and Coelli (1995) which is implicitly defined in Equation 4:

$$U_{it} = \delta_0 + \delta_i Z_{it} \qquad (4)$$

In this equation, U_{it} represents technical inefficiency, δ_0 is an unknown parameter vector, δ_i is the parameter vector to be estimated, and Z_{it} denotes explanatory variables related to the effects of technical inefficiency. Equation 5 represents the stochastic production function with a disturbance term:

$$Y_i = f(X\beta) + e_i \qquad (5)$$

In this equation, Y is agricultural output in rupiah, X is the vector of input prices, β is the parameter vector, and e is the stochastic disturbance term consisting of two independent elements, u and v:

$$e_i = v - u \qquad (6)$$

The fundamental assumption underlying the estimation of the production function in Equation 5 is that all farmers, whether cooperative members or not, have uniform access to technology. However, this assumption is not applicable in this study due to the diverse characteristics of farmers, both observable and unobservable, that influence their decision to either join or refrain from joining the cooperative (Ma et al., 2018; Mojo et al., 2017; Wossen et al., 2017). Consequently, farmers who become cooperative members may face different production frontiers compared to non-members. This endogeneity in the decision to become a cooperative member necessitates an analysis to address selectivity bias in estimating TE among rice farmers. The PSM method can be utilized to achieve this.

3.3. Propensity Score Matching

This study aims to compare the efficiency of cooperative member farmers with those not affiliated with a cooperative. In deciding to join a cooperative, farmers encounter distinct production functions, indicating that the choice to join is flexible. As a result, an analysis that compares the TE between cooperative members and non-members must consider the potential for selection bias among farmers.

We hypothesize that farmers' decisions to join a cooperative are influenced by comparing the potential benefits derived from this decision. Specifically, farmers are likely to opt for cooperative membership if the perceived benefits surpass those available to non-members. Though not directly observable, these benefit differentials can be inferred from farmers' decisions to join the cooperative, which are, in turn, influenced by their demographic and social characteristics. Employing a matching method to compare cooperative members with non-members with similar characteristics can effectively address the issue of selection bias (Ito et al., 2012; Ma & Abdulai, 2016, 2017; Ma et al., 2018).

The benefits of becoming a cooperative member, which can be expressed as a function of observable characteristics, are integrated into the latent variable model as follows:

$$C_i^* = \beta Z_i + \varepsilon_i \qquad (7)$$

where C_i^* is the cooperative membership indicator and ε_i is the random error. The dependent variable representing cooperative membership status—where $C_i = 1$ for cooperative members and $C_i = 0$ for non-members—can be explained as follows:

$$C_i = \begin{cases} 1 \text{ if } C_i^* > 0 \\ 0 \text{ otherwise} \end{cases} \qquad (8)$$

In observational research involving a treatment group and a control group whose covariates the researcher can observe, matching methods serve as tools to address selection bias. If the researcher can observe covariate differences between these two groups, matching can yield unbiased impact evaluations. The PSM method generates a propensity score, a scalar dimension of observed covariates (Rosenbaum & Rubin, 1985). This research selects and matches group members with the same propensity score (Mojo et al., 2017). Here's how to estimate the propensity score:

$$p(Z_i) = \text{Prob}(C_i = 1|Z_i) \qquad (9)$$

where the propensity score $p(Z_i)$ is estimated using a logit model that regresses cooperative membership on the socioeconomic characteristics of the household.

The next step is to determine an appropriate matching estimator. The literature discusses several matching methods, such as the neighbor, kernel, and radius methods. A good method should not discard too many original observations and maintain the same mean covariates between the households in the treatment and control groups (Abebaw & Haile, 2013).

Furthermore, we estimate the average treatment for the treated (ATT), demonstrating the impact of cooperative membership on efficiency. Heinrich, Maffioli, and Vázquez (2010) express this through the following equation:

$$ATT = \mathrm{E}\{Y_{1i} - Y_{0i}|C_i = 1\} = E[E\{Y_{1i} - Y_{0i}|C_i = 1, p(Z_i)\}]$$
$$= E[E\{Y_{1i}|C_i = 1, p(Z_i)\} - E[E\{Y_{0i}|C_i = 0, p(Z_i)\}]|C_i = 1] \quad (10)$$

where Y_1 and Y_0 are the outcome variable values for cooperative members and non-members, respectively, and i represents households.

PSM operates under several assumptions. Initially, PSM operates under the assumption of conditional independence (CIA), which asserts that once we control for observable covariates (Z), potential outcomes become independent of treatment assignment.

This assumption presupposes that membership decisions are solely based on observable characteristics, allowing the detection of variables that simultaneously influence both the decision and performance indicators. Second, we assume the achievement of common support, which signifies an overlap in the propensity score distribution between the treatment and control groups.

Lastly, PSM necessitates balance, or the balancing property, ensuring that the mean values of covariates for both members and non-members are identical after matching. This condition aims to confirm that treatment is not contingent on unit characteristics after conditioning on Z (Heinrich et al., 2010).

4. RESULTS AND DISCUSSION

4.1. Descriptive Statistics

The proportion of farmers who are members of the cooperative constitutes only 2.08 percent of the total sample. This sample includes 57,077 farmers engaged in cultivation during the wet season. However, this percentage increases slightly during the dry season to 2.66 percent. These figures indicate that the interest of farmers in becoming cooperative members could be much higher.

Table 3 details the number of samples in the treatment and control groups. The treatment group comprises cooperative members, while the control group comprises non-cooperative ones.

Table 3. Cooperative members vs. non-members.

Description	Wet season	Dry season
Non-members	55,888	10,656
Members	1,189	291
Total	57,077	10,947

Note: This table displays the number of cooperative member and non-member households.
Source: Badan Pusat Statistik (2014).

Table 4 presents the socioeconomic characteristics and variables used to estimate TE. These include age, gender, and education level to determine the household head's characteristics. In each household, we also controlled for land ownership status and size, house ownership status and size, and electricity usage. In addition to the descriptive statistics of socioeconomic characteristics, we tested the mean differences between cooperative members and non-members to identify potential bias in our sample.

Table 4. Socioeconomic characteristics and variables of stochastic frontier analysis.

Variables	Description
Characteristics	
Age	Age of the household head (Years)
Gender	Gender of the household head (1 = Male, 0 = Female)
Education	Education level of the household head (1 = Did not finish primary school, 2 = Completed primary school, 3 = Completed middle school, 4 = Completed high school, 5 = Diploma-1 degree, 6 = Diploma-3 degree, 7 = Bachelor's degree, 8 = Master's degree or above)
Land ownership	The household has its own agricultural land (1 = Yes, 0 = Otherwise)
Land size	Agricultural land area (m^2)
House ownership	The household owns its own house (1 = Yes, 0 = Otherwise)
House size	House area (m^2)
Electricity	The household uses electricity (1 = Yes, 0 = Otherwise)
Variables of stochastic frontier analysis	
Production	The value of rice production (Rp/ha) in log
Seeds	The cost of procuring rice seeds (Rp/ha) in log
Fertilizers	The cost of fertilizer (Rp/ha) in log
Pesticides	The cost of pesticides (Rp/ha) in log
Wages	Labor wages (Rp/ha) in log
Agricultural expenses	Agricultural expenses, such as equipment rental, fees, and taxes (Rp/ha) in log
Other expenses	Other expenses (Rp/ha) in log

Source: Badan Pusat Statistik (2014).

Table 5 shows the mean and mean differences within our research sample for the wet season. The average age of household heads is 50.3 years for cooperative members and 49.8 years for non-members. Most of these heads are male, comprising 92 percent of members and 89 percent of non-members. The majority of cooperative member household heads have a significantly higher educational level, with most having completed at least primary school. Regarding land ownership, 68 percent of members own land, compared to 71 percent for non-members, suggesting that cooperative members generally own less land. However, members manage an average land size that is larger than that of non-members. House ownership is similar across both groups, at 96 percent. Nonetheless, cooperative members tend to have larger houses on average. Additionally, members use more electricity than non-members, at 98 percent compared to 96 percent.

Table 5. Descriptive statistics for the wet season.

Variables	Members (N = 1,189)		Non-members (N = 55,888)		Mean diff.
	Mean	Std err	Mean	Std err	
Age	50.313	0.337	49.786	0.051	0.527
Gender	0.921	0.008	0.886	0.001	0.035***
Education	2.410	0.036	2.231	0.005	0.179***
Land ownership	0.682	0.014	0.716	0.002	−0.034***
Land size	0.521	0.017	0.448	0.002	0.073***
House ownership	0.961	0.005	0.959	0.001	0.002
House size	85.468	2.295	79.159	0.395	6.309**
Electricity	0.982	0.004	0.959	0.001	0.023***
Production	16.611	0.013	16.433	0.002	0.178***
Seeds	3.513	0.017	3.435	0.003	0.078***
Fertilizers	13.869	0.018	13.739	0.003	0.130***
Pesticides	12.169	0.037	12.107	0.005	0.062*
Wages	15.026	0.020	15.182	0.003	−0.156***
Agricultural expenses	14.576	0.026	14.336	0.004	0.240***
Other expenses	15.093	0.019	14.936	0.003	0.157***

Note: This table highlights the mean differences in the socioeconomic characteristics of farmers and production frontier variables during the wet season, signifying notable distinctions between cooperative and non-cooperative members.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Similarly, the production frontier variables reveal significant mean differences between cooperative members and non-members. The outcomes of the statistical analysis suggest that cooperative member farmers generally experience better socioeconomic conditions than non-member farmers, except for age and house ownership. Overall, the data suggests that cooperative members have a higher level of well-being during the wet season compared to their non-member counterparts.

Table 6. Descriptive statistics for the dry season.

Variables	Members (N = 291)		Non-members (N = 10,656)		Mean diff.
	Mean	Std err	Mean	Std err	
Age	51.460	0.649	49.644	0.116	1.816**
Gender	0.917	0.016	0.888	0.003	0.029
Education	2.477	0.074	2.229	0.011	0.248***
Land ownership	0.667	0.027	0.710	0.004	−0.043
Land size	0.429	0.030	0.459	0.004	−0.030
House ownership	0.966	0.010	0.960	0.001	0.006
House size	84.615	2.528	76.872	0.589	7.743**
Electricity	0.983	0.007	0.952	0.002	0.031**
Production	16.656	0.022	16.437	0.005	0.219***
Seeds	3.530	0.032	3.406	0.005	0.124***
Fertilizers	13.841	0.045	13.701	0.006	0.140***
Pesticides	12.433	0.054	12.061	0.013	0.371***
Wages	15.102	0.042	15.166	0.006	0.064
Agricultural expenses	14.665	0.047	14.327	0.010	0.338***
Other expenses	15.233	0.031	14.936	0.007	0.297***

Note: This table highlights the mean differences in the socioeconomic characteristics of farmers and production frontier variables during the wet season, signifying notable distinctions between cooperative and non-cooperative members.
*** $p < 0.01$, ** $p < 0.05$.

Table 6 shows the mean and mean differences in our research sample for the dry season. The average age of household heads is 51.5 years for cooperative members and 49.6 years for non-members. Most of these heads are male, comprising 92 percent of members and 89 percent of non-members. The educational level among cooperative member household heads is higher compared to non-members, with most having completed at least primary school. Land ownership status stands at 67 percent for members and 71 percent for non-members, indicating that cooperative members own less land. Moreover, members manage a smaller land area, averaging 0.43 hectares, compared to 0.46 hectares for non-members. The proportion of members who own a house mirrors that of non-members, at around 96 percent. However, cooperative members typically have larger houses, with an average area of 84.6 square meters, compared to 76.8 square meters for non-members. Additionally, members use more electricity than non-members, at 98 percent versus 95 percent.

The production frontier variables also reveal significant mean differences between cooperative members and non-members. The statistical analysis results suggest that cooperative member farmers generally enjoy better socioeconomic conditions than non-member farmers, with exceptions in land ownership status, land size, and house ownership. Observing the descriptive results for farmers in both wet and dry seasons reveals substantial mean differences between cooperative members and non-members, potentially indicating the presence of selectivity bias. This study addresses this problem by utilizing a matching approach.

4.2. Technical Efficiency

We employ the Stochastic Frontier Analysis (SFA) method to gauge the technical efficiency of farmers in managing their agricultural enterprises. This method entails an initial specification, often utilizing well-established functions such as Cobb–Douglas and translog. The Cobb–Douglas function, a specific variant of the translog production function, assumes that the coefficients of squares and interaction terms from the translog frontier are set to zero (Adeyemi et al., 2017).

In this study, we apply the maximum likelihood (ML) technique to estimate the parameters of the stochastic frontier. The model includes explanatory variables that gauge inefficiency, allowing an assessment of technical efficiency. The results of the ML test are then utilized to compare the translog and Cobb–Douglas models, determining the most suitable model for this research.

The Cobb–Douglas model is as follows, based on the model used by Anang, Bäckman, and Rezitis (2017) and Bibi et al. (2021):

$$lnY_i = \beta_0 + \sum_{j=1}^{n} \beta_j lnX_{ji} + v_i - u_i \quad (7)$$

The translog production frontier model, following Tipi, Dari, and Vural (2021) and Bai, Salim, and Bloch (2019) is expressed as follows:

$$the\ lnY_i = \beta_0 + \sum_{j=1}^{n} \beta_j lnX_{ji} + \sum_{j=1}^{n} \sum_{k=1}^{n} \beta_{jk} lnX_{ji} lnX_{ki} + v_i - u_i \quad (8)$$

Here ln represents the natural logarithm and Y_i denotes the rice production (Rp/ha). We opted to use the value of production over the weight of the harvest, as it more accurately reflects differences in crop quality (Ma et al., 2018). X_i denotes the vector of input variables, including the costs of rice seeds, fertilizer, pesticides, agricultural expenses, labor wages, and other costs (Rp/ha); β_0 is the constant; β_j and u_i are estimated parameters; and v_i is the random error.

Both functional models, Cobb–Douglas and translog, were tested to determine the best fit for this research. The model fit was evaluated using the ML-ratio estimator. To compare the two models, the likelihood-ratio (LR) statistic, as described by Coelli et al. (2005) is used:

$$LR = -2\{ln[L(H_0)] - ln[L(H_1)]\} \quad (9)$$

In this equation, LR represents the LR statistic. $\ln[L(H_0)]$ is the logarithm of the likelihood for the restricted Cobb–Douglas model (H0), assuming it is the most suitable. Furthermore, $\ln[L(H_1)]$ is the logarithm of the likelihood for the unrestricted translog model (H1), assuming it is more appropriate for this research. The ML ratio is assumed to follow a Chi-square distribution.

Following a Chi-square distribution during the wet season, the estimation results for the LR test show a statistically significant value of 811.46 at the 1% level. This figure exceeds the critical value of 38.30 with 21 degrees of freedom (Kodde & Palm, 1986). Similarly, in the dry season, the LR test's estimation results reveal a statistically significant value of 180.39 at the 1% level. Consequently, H0 is rejected, suggesting that the translog model is more appropriate for this research than the Cobb–Douglas model. The translog model offers several benefits over the Cobb–Douglas model. For instance, unlike the Cobb- Douglas function, the translog function does not assume perfect substitution between input factors. Additionally, while the Cobb–Douglas function presumes constant returns to scale—a concept that may be challenging to substantiate in reality—the translog function allows greater flexibility in modeling production relationships. These benefits render the translog model an effective tool for analyzing real-world production processes, often requiring more complex interactions between input factors (Bibi et al., 2021; Tipi et al., 2021).

Table 7 presents the results of farmers' technical efficiency during the wet and dry seasons. In the wet season, fertilizer and labor wages significantly and positively affect efficiency, indicating that higher fertilizer usage and wages increase efficiency. The positive interaction indicates a complementary relationship. Variable complementarity is only evident in the use of pesticides and labor wages, where an increase in pesticide usage corresponds to an increase in labor wages. We understand this as the use of pesticides requiring additional implementation costs, thereby increasing labor wages. The negative interaction between cost variables indicates a substitutive relationship. Most variables exhibit substitutive relationships, such as the interactions between fertilizer and labor wages, agricultural costs, and other expenses. This suggests that efficient fertilizer usage can lower labor wages, agricultural costs, and other expenses that farmers incur. Similarly, there is a substitutive relationship between labor wages, agricultural costs, and other expenses.

Table 7. Technical efficiency.

Variables	Wet season	Dry season
Seeds	−0.044 (0.159)	1.875 (0.386)***
Fertilizers	0.986 (0.166)***	0.585 (0.382)
Pesticides	−0.085 (0.079)	−0.214 (0.175)
Wages	0.301 (0.168)*	0.032 (0.412)
Agricultural expenses	−0.422 (0.111)***	−0.373 (0.277)
Other expenses	−0.344 (0.146)**	−1.912 (0.329)***
Seeds x seeds	0.026 (0.004)***	0.012 (0.012)
Seeds x fertilizers	−0.006 (0.008)	−0.092 (0.019)***
Seeds x pesticides	0.001 (0.003)	−0.007 (0.007)
Seeds x wages	0.001 (0.007)	−0.061 (0.017)***
Seeds x agricultural expenses	−0.005 (0.005)	−0.016 (0.012)
Seeds x other expenses	0.002 (0.006)	0.037 (0.015)**
Fertilizers x fertilizers	0.036 (0.003)***	0.021 (0.007)***
Fertilizers x pesticides	−0.001 (0.004)	0.002 (0.008)
Fertilizers x wages	−0.058 (0.007)***	−0.041 (0.017)**
Fertilizers x agricultural expenses	−0.034 (0.005)***	−0.035 (0.012)***
Fertilizers x other expenses	−0.025 (0.007)***	0.027 (0.016)*
Pesticides x pesticides	−0.002 (0.001)***	0.001 (0.001)
Pesticides x wages	0.008 (0.003)***	−0.001 (0.007)
Pesticides x agricultural expenses	0.011 (0.002)	0.013 (0.006)**
Pesticides x other expenses	−0.009 (0.002)***	0.001 (0.006)
Wages x wages	0.035 (0.004)	0.034 (0.009)***
Wages x agricultural expenses	−0.016 (0.005)***	−0.010 (0.013)
Wages x other expenses	−0.019 (0.006)***	0.001 (0.015)
Agricultural expenses x agricultural expenses	0.041 (0.002)***	0.031 (0.006)***
Agricultural expenses x other expenses	−0.003 (0.004)	0.006 (0.011)
Other expenses x other expenses	0.043 (0.003)***	0.047 (0.009)***
Constant	9.789 (2.233)***	23.633 (5.133)***
U sigma	0.337 (0.003)***	0.366 (0.008)***
V sigma	0.250 (0.002)***	0.262 (0.005)***
Lambda (λ)	1.346 (0.005)***	1.396 (0.012)***
Log likelihood	−12,740	−2,760.05
Wald Chi-square	8,657.99	1,390.67

Note: This table displays the results of the SFA for agriculture during the wet and dry seasons.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

During the dry season, the positive and significant coefficient for seeds implies that higher expenditures by farmers on seeds lead to increased efficiency. Positive interactions, indicating complementary relationships, are observed between the variables of seeds and other expenses and between pesticides and agricultural costs. This phenomenon can be explained by increasing the use of seeds and pesticides, which also increases agricultural costs and other expenses.

Negative interactions, indicating a substitution relationship between variables, are found in the relationships between seeds and fertilizer and between seeds and labor wages. We observe positive interactions, indicating complementary relationships, between the variables of seeds and other expenses, as well as between pesticides and agricultural costs. We can explain this phenomenon by increasing the use of seeds and pesticides, which in turn increases agricultural costs and other expenses.

Figure 1 displays the efficiency values for the two seasons under investigation: the wet season and the dry season. Approximately 40 percent of farmers have technical efficiency values ranging from 80 to 90 percent in both seasons. Additionally, nearly 25 percent of farmers fall within the 70 to 80 percent efficiency range in both the wet and dry seasons.

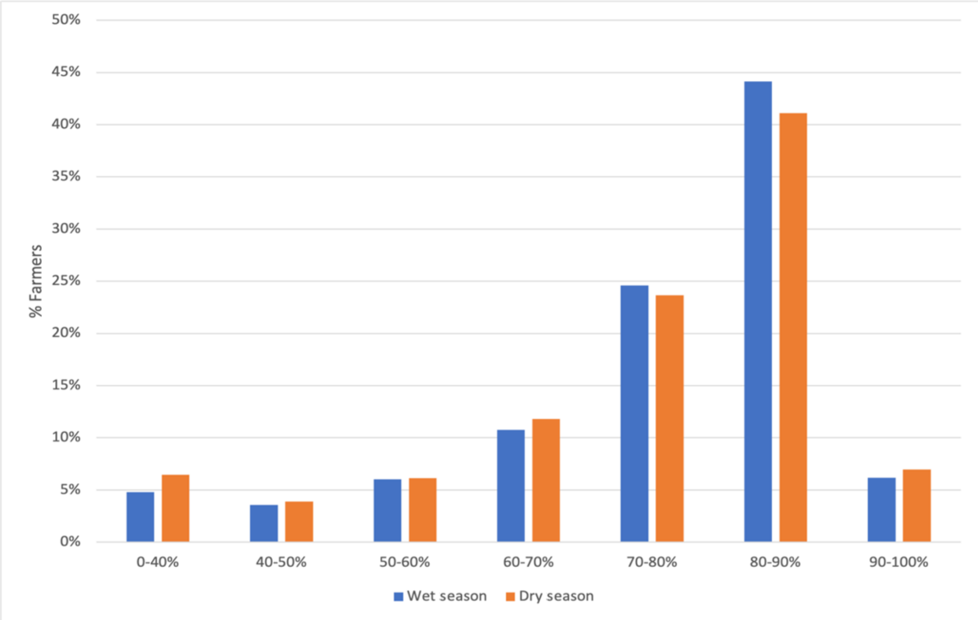
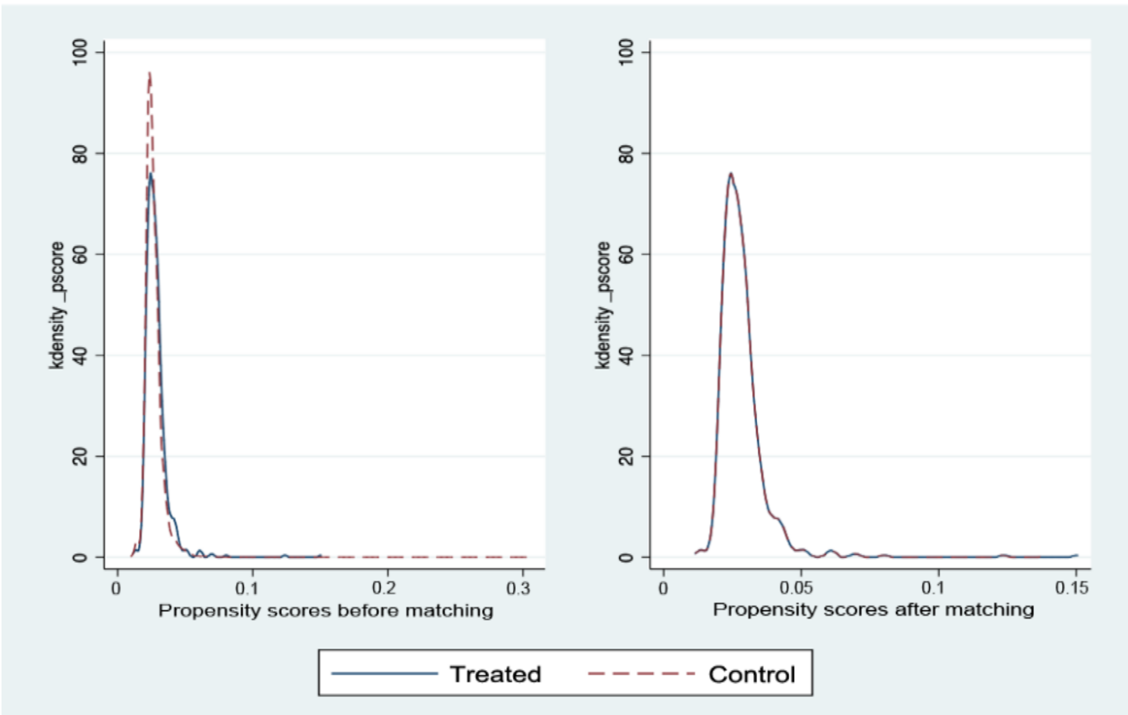


Figure 1. Efficiency score distribution using stochastic frontier analysis.

4.3. Propensity Score Matching

In the next step, we compared the technical efficiency results from the SFA. Using the nearest-neighbor (1) method for matching analysis, we aimed for one-to-one matches. We then compared the matching results between the treatment and non-treatment groups. In the wet season, the non-treatment group, consisting of non-cooperative members, included 55,888 households, while the treatment group, comprising cooperative members, included 1,189 households. During the dry season, the number of farmers in agriculture decreases due to the dependence on rainfall for water. Those continuing their activities in the dry season usually have irrigated land, allowing for year-round cultivation. The number of non-cooperative member farmers in the dry season was 10,656 households, compared to 291 cooperative member farmers.



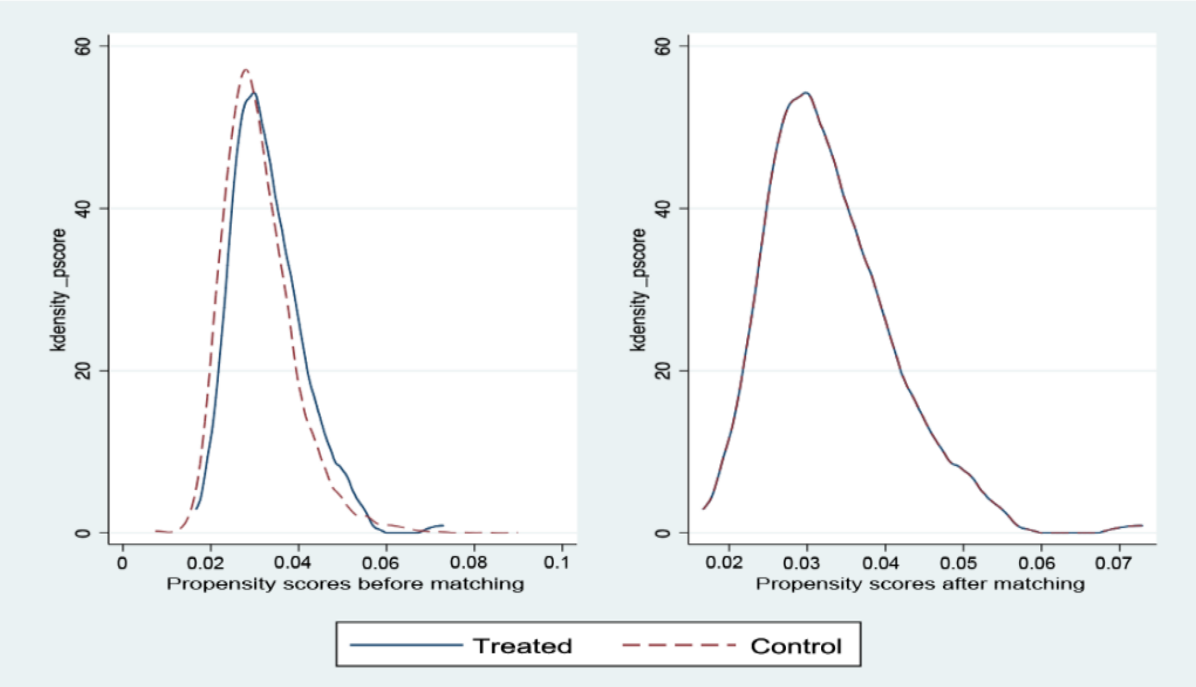


Figure 2. Pscore before and after propensity score matching.

Note: (a) The upper figure displays the Pscores for the wet season, and (b) the lower figure illustrates the Pscores for the dry season. The matching of the control and treatment groups was executed using the nearest-neighbor (1) method.

The common support area indicates a positive density range from the distribution of the treatment and control groups, which spans from 0.009 to 0.306 during the wet season. In the dry season, this distribution ranges from 0.007 to 0.089. Greene's value for the correction term for selectivity is subsequently calculated and integrated into the stochastic frontier model based on the propensity scores (Ma et al., 2018). As depicted in Figure 2, the propensity scores post-matching exhibit greater similarity than those before matching.

Table 8. Propensity score matching analysis.

Variables	Wet season		Dry season	
	Coef.	Std. err.	Coef.	Std. err.
Age	0.003	0.003	0.020***	0.007
Gender	0.130	0.136	0.213	0.295
Education	0.118***	0.030	0.133**	0.067
Land ownership	−0.178**	0.083	−0.145	0.180
Land size	0.245***	0.068	−0.084	0.211
House ownership	0.208	0.215	0.011	0.473
House size	0.001*	0.0002	−0.001	0.001
Electricity	0.496	0.383		
Constant	−4.896***	0.477	−4.764***	0.668
Chi-square	38.22		10.30	
Log likelihood	−3,189.71		−667.77	
ATT difference	0.021***		0.031**	
Control	25,391		4,712	
Treated	696		151	

Note: This table presents the PSM analysis using the nearest-neighbor (1) method, showing the ATT results following the Battese and Coelli (1995) method.
***p < 0.01, **p < 0.05, *p < 0.1.

Table 8 displays the matching results, integral to the impact analysis contrasting the treatment and non-treatment groups. The ATT during the wet season registers at 0.021, a positive and statistically significant figure. This suggests that cooperative member farmers' efficiency levels exceed those of non-member farmers by 2.1 percent. Similarly, the dry season's ATT reveals a positive and significant figure of 0.031. This figure denotes that cooperative member farmers achieve an efficiency of 3.1 percent greater than their non-member counterparts.

Table 8 indicates sufficient evidence to affirm that both hypotheses, namely, the socioeconomic characteristics of households influencing the decision to become cooperative members and cooperative membership positively impacting farmer efficiency, are substantiated among rice farmers in Indonesia.

4.4. Discussion

The technical efficiency of farmers, as depicted in Table 7, reveals the impact of production factors on efficiency. It is evident that during the wet season, fertilizer utilization and labor wages contribute to an increase in efficiency. The improvement in fertilizer use involves not only an increase in quantity but also an enhancement in quality. We can interpret the rise in labor wages as an improvement in the well-being of agricultural workers, which in turn influences the enhancement of their performance. This positive impact of fertilizer and labor wages on efficiency aligns with findings on rice production efficiency in Ghana and Uganda (Akite et al., 2022; Anang et al., 2017), in China (Ma et al., 2018), and in Pakistan (Khan et al., 2022). Conversely, agricultural costs and other expenses have a negative and significant impact on efficiency. This is consistent with the research in Uganda (Akite et al., 2022) suggesting that higher agricultural costs and other expenses tend to decrease farmers' efficiency.

In the dry season, the results from Table 7 suggest that increased expenditures by farmers on seeds result in enhanced efficiency. This is consistent with research findings regarding rice farmers in Uganda (Anang et al., 2017). The cost of purchasing seeds relates to quantity and quality, with higher-quality seeds tending to be more expensive. The negative coefficient for other expenses suggests that reducing these costs could increase farmer efficiency (Akite et al., 2022; Bibi et al., 2021).

Table 7 also shows the legit sample selection model results for cooperative membership choice. The empirical data indicates that education level, land ownership status, and land size significantly influence cooperative membership. These findings align with similar research in China (Ito et al., 2012; Ma et al., 2018) and Ethiopia (Mojo et al., 2017). A higher education level expands farmers' perspectives, encouraging them to adopt modern practices and join cooperatives. Furthermore, land ownership status and size are key motivators for joining cooperatives to enhance land management. Agricultural cooperatives aid farmers in managing their land and boosting efficiency through technologies that increase yields, such as fertilizers and pesticides, leading to enhanced agricultural productivity and income.

Higher seed prices can reduce fertilizer, labor costs, and overall agricultural expenses. Improving the quality of the seeds farmers use can lead to better yields (Anang et al., 2017; González-Flores et al., 2014). Quality seeds require less fertilizer, ultimately reducing labor and other agricultural costs. The negative interactions between these variables indicate a substitutive relationship, demonstrating that planting high-quality seeds leads to improved yields.

Using top-quality fertilizers can enhance farmers' efficiency. While higher fertilizer costs support increased production yields, higher prices do not necessarily correlate with the quantity of fertilizer used. Farmers should use higher-quality fertilizers, which result in lower quantities required but yield higher quality. Opting for organic fertilizers of superior quality can be a viable option to boost efficiency. According to these results, improving farmers' access to quality fertilizers contributes significantly to rice production (Anang et al., 2017; Khan et al., 2022).

Moreover, the interaction between fertilizer use and farming costs yields a negative value, suggesting that increased fertilizer usage will decrease farming costs. Higher-quality fertilizer will reduce other expenses, yielding overall cost savings and minimizing negative impacts. Contrarily, pesticide usage does not affect farmers' efficiency. However, in terms of their interaction, increasing pesticide usage raises farming costs, indirectly impacting efficiency.

The ATT findings in Table 8 are consistent with other findings from ample research on the role of cooperatives among sweet potato farmers in Nigeria (Onuwa et al., 2021) and on apple farmers in China (Ma et al., 2018), indicating that cooperative members have a higher TE than non-members. These results also support organizational theory, suggesting reduced transaction costs when businesses collaborate (Williamson, 2002, 2010). By working together, farmers can acquire input factors at lower costs and sell their produce at higher prices than if operating individually. These reduced transaction costs allow optimal output production with minimal inputs. However, these findings contradict and complement those of Hasan, Azhari, and Majid (2018), who reported high inefficiency in Indonesian cooperatives. Their study, which was based on aggregate firm-level data, may only partially reflect changes at the household level.

4.5. Robustness Test

We estimated the model using an alternative method, coarsened exact matching (CEM), to test its robustness. Despite its widespread use, PSM may exacerbate imbalance, inefficiency, and bias in models (King & Nielsen, 2019). Researchers can choose the balance between the treated and control groups ahead of time with coarsened exact matching, a monotonic matching method that lowers imbalance (Blackwell, Iacus, King, & Porro, 2009; Iacus, King, & Porro, 2012). In its application, coarser exact matching is easier to comprehend and requires fewer assumptions. Furthermore, we can combine it with other matching methods.

The core principle of CEM is to limit imbalances. By choosing to limit imbalance ex-ante, researchers enforce tighter bounds. Additionally, CEM offers several advantages. First, it adheres to the congruence principle, ensuring that the data size matches the analysis. Second, it directly restricts data to guarantee common support. Lastly, CEM is computationally efficient.

CEM solely performs matching between the treated and control groups. Researchers can employ other regression methods to estimate ATT, such as additional matching methods or ordinary least squares (OLS). Ensuring that the dataset used is authentic (Blackwell et al., 2009) is crucial.

Table 9. CEM–PSM and CEM–OLS analysis.

Variables	CEM-PSM		CEM-OLS	
	Wet season	Dry season	Wet season	Dry season
Age	0.007* (0.003)	0.027*** (0.009)	0.0003*** (0.000)	0.0008*** (0.0002)
Gender	−0.187 (0.138)	−0.609* (0.319)	−0.004 (0.003)	0.001 (0.011)
Education	0.190*** (0.033)	0.259*** (0.086)	0.008*** (0.001)	0.014*** (0.003)
Land ownership	−0.222*** (0.085)	−0.174 (0.190)	−0.0005 (0.002)	0.012** (0.006)
Land size	0.355*** (0.084)	0.238 (0.283)	−0.008*** (0.002)	−0.010 (0.009)
House ownership	−0.525** (0.220)	−1.612*** (0.531)	−0.009 (0.007)	0.038 (0.033)
House size	0.001** (0.0007)	0.002 (0.002)	0.00003* (0.00002)	−0.0002** (0.0001)
Electricity	−0.901** (0.424)		0.018 (0.014)	−0.027 (0.061)
Cooperative			0.031*** (0.006)	0.044*** (0.013)
Constant	−2.863*** (0.523)	−3.159*** (0.822)	0.711*** (0.017)	0.656*** (0.072)
Chi-square	67.89	26.51		
R-square	0.0108	0.0217	0.0052	0.0117
ATT difference	0.032*** (0.007)	0.074*** (0.018)		
Control	23,312	3,437	50,380	7,431
Treated	691	146	1,180	277

Note: This table displays the results of the CEM–PSM and CEM–OLS analyses using the same dataset as a robustness test.
***p < 0.01, **p < 0.05, *p < 0.1.

Table 9 presents the CEM–PSM and CEM–OLS analyses. The CEM–PSM analysis integrates two matching methods: CEM followed by ATT estimation using PSM. Since CEM does not automatically calculate ATT, an additional method is required. A notable difference is the increased importance of the control variables compared to using only the PSM method. The number of respondents in the CEM-PSM analysis slightly decreased compared to using PSM alone. For instance, the wet season saw a reduction in the control group from 25,391 to 23,312 respondents, and a reduction in the treatment group from 696 to 691 respondents. In the dry season, the control group decreased from 4,712 to 3,437 respondents, and the treatment group decreased from 151 to 146 respondents. The ATT difference, however, does not show significant changes. ATT is 3.2 percent in the wet season, and in the dry season, it is 7.4 percent—an increase compared to using only the PSM method.

The estimation results of ATT using the CEM–OLS method are indicated by the dummy variable "cooperative," representing the contribution of cooperative membership to TE. The "cooperative" variable shows positive and significant figures of 3.1 percent and 4.4 percent in the wet and dry seasons, respectively. These results align closely with the ATT estimates from the PSM or CEM–PSM models. This consistency across different methods affirms the robustness of the research findings.

5. CONCLUSION AND IMPLICATIONS

5.1. Conclusion

This study estimates the impact of cooperative membership on Indonesia's farmers' technical efficiency. We measure technical efficiency by adopting the SFA method. We analyze cross-sectional data from the BPS, comprising 68,204 selected samples. The SFA results indicate that using quality seeds and fertilizers enhances efficiency. In this context, "quality" encompasses not only the quantity of fertilizers but also their environmentally friendly nature. Despite these efficiency advantages, the number of farmers willing to join cooperatives remains modest. Socioeconomically, more prosperous farmers—those with higher education, larger agricultural land holdings, and bigger homes—are more likely to choose cooperative membership.

The results are then compared between treated and untreated samples using the PSM method, which addresses potential selectivity bias in the decision to join a cooperative. PSM compares the technical efficiency of cooperative members with their non-member counterparts. We also account for the significance of seasonality, specifically, the efficiency during wet and dry seasons, in our estimations. The findings, presented as ATT, show that cooperative members are more efficient than non-members during both seasons. Specifically, cooperative members exhibit 2.1 percent higher efficiency in wet seasons and 3.1 percent in dry seasons. The results using the CEM method corroborate these findings.

The presence of cooperatives positively impacts members by allowing them to reduce the purchase prices of the necessary inputs and increase the selling prices of their harvest. Cooperatives also shield their members from exploitative practices and usurious systems, improving farmers' welfare.

5.2. Policy Implications

This research offers some significant policy implications regarding cooperative membership and its impact on agricultural efficiency. First, the government and other stakeholders should step up strategies to enhance and refine the governance framework for the facilitation of improved distribution of seeds and fertilizers. Using good seeds and fertilizers has been demonstrated to enhance efficiency; thus, the government should facilitate farmers' access to high-quality seeds and fertilizers.

Second, cooperatives have proven effective in enhancing farmer efficiency. They can act as an extension of the government, providing farmers with guidance, education, and protection. Therefore, the development and support of cooperatives are crucial to boosting the overall welfare of farmers. Education levels and land ownership, indicators of farmers' well-being, are key motivators for individuals to join agricultural cooperatives. The government should encourage farmers to pursue higher education levels. This effort would indirectly enhance their understanding of the benefits of joining cooperatives, which are instrumental in improving their welfare. Additionally, policies aimed at organizing agricultural land in rural areas warrant further examination as they can support increased efficiency in the agricultural sector.

5.3. Limitations of Study

One limitation of this study lies in the possible presence of additional informal associations beyond the cooperatives adhered to by farmers. As a result, individuals who are not cooperative members may still experience similar benefits from participating in collective farming practices within farmer groups.

Data constraints are a notable limitation of this research. This research limits the available data to a single time period, which only allows for cross-sectional analysis. This limitation implies that the derived conclusions may not comprehensively encompass temporal changes, in contrast to the analysis of panel or longitudinal data.

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