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Are farmer-based organizations still relevant? Evaluating the impact of farmer-group participation on maize productivity in Indonesia

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ABSTRACT

Maize production contributes significantly to Indonesia's economic development, but the sector faces a classic challenge: rising demand and low productivity. Support from a farmer-based organization (FBO), commonly referred to as a farmer group, is a key institutional factor that can enhance productivity. It can, among others, increase farmers' access to the input and output markets. However, it is also argued that the role of an FBO in agricultural development depends on its capabilities and institutional support. On the empirical front, evidence on the impact of farmer-group membership remains inconclusive. This study examines the causal effect of farmer-group participation on maize productivity in Indonesia using the propensity score matching (PSM) method and dataset from the Indonesian Secondary Food Crops Cultivation Farm Household Survey by Statistics Indonesia. The PSM estimation indicates that farmer-group participation increases maize productivity by 0.095 to 0.195 t/ha, equivalent to approximately 2.2–4.4% improvement relative to non-members. It indicates that FBOs remain relevant in agricultural development policy in Indonesia.

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1. Introduction

The agricultural sector plays a central role in Indonesia's economic development. In 2025, it contributed 13.10% of the national gross domestic product (GDP) and generated employment for nearly 39 million people, equivalent to 29% of the total workforce (Statistics Indonesia, 2022a, 2022b). Growth in the agricultural sector has contributed to poverty reduction, particularly in rural areas where poverty rates have been disproportionately high (Suryahadi et al., 2012). It also offers a viable solution to food insecurity in Indonesia, which, according to the Global Food Security Index, ranked 65th out of 113 countries, lagging other ASEAN members such as Malaysia, Thailand, and Vietnam (Abdurrahman et al., 2027; Asian Development Bank [ADB], 2019). However, sustaining this role requires continuous improvements in agricultural productivity, which is shaped not only by conventional inputs such as land, labor, and capital, but also by institutional factors that influence farmers' access to resources, information, and markets. Among these institutional mechanisms, Farmer-Based Organizations (FBOs) are increasingly recognized as a key driver of productivity improvements.

Maize is a key agricultural commodity in Indonesia, with approximately 20% or 5 million farm households depending on maize cultivation for their livelihoods (Haryanto, Wardana, Jamil, et al., 2023; Haryanto, Wardana, & Basconcillo, 2023; Ministry of Trade, 2017; PISAgro, 2016). In 2019, the annual maize production reached approximately 30 million tons, making Indonesia the sixth-largest maize producer globally (FAO, 2021). The output is both for direct consumption and animal feed (Ministry of

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Agriculture, 2020; PISAgro, 2016), so the availability also affects the stability of other products, such as poultry and beef (PISAgro, 2016).

Despite efforts to optimize maize production, the domestic supply continues to fall short of demand (Haryanto, Wardana, Jamil, et al., 2023; Haryanto, Wardana, & Basconcillo, 2023; Magfiroh et al., 2018). Between 2009 and 2018, the average annual maize supply was around 9 million tons, while demand reached 11 million tons per year (Freddy et al., 2018). Indonesia imported nearly 1 million tons of maize in 2021, an increase of around 15% from the previous year (Statistics Indonesia, 2022c). Expanding maize cultivation areas or extensification faces challenges due to rapid urbanization, especially on Java Island, where agricultural land is increasingly scarce (Suwandari et al., 2020). Irrigation systems in dryland regions are also inadequate (Ruslan, 2021; Wangiyana & Kusnarta, 2020). Given these challenges, intensification appears to be a more viable solution.

While Indonesia's maize productivity has improved over the years, it remains lower than other major maize-producing countries. In 2024, its productivity stood at approximately 5.9 tons per hectare (t/ha), compared to 11.2 t/ha in the US, 6.6 t/ha in China, and 6.1 t/ha in Cambodia (Ritchie et al., 2026). Additionally, there are productivity disparities between farmers in Java and those in other regions. In 2023, the productivity rate outside Java (5.7 t/ha) was 13% lower than that on Java (6.2 t/ha) (Ministry of Agriculture of Indonesia, 2024). These gaps highlight the need for more effective strategies to enhance agricultural productivity.

In Indonesia, Farmer-Based Organizations (FBOs), commonly referred to as farmer groups (*kelompok tani*), constitute a key institutional component of the agricultural development framework. FBOs play an important role in implementing government agricultural programs, particularly those related to extension services, input distribution, and technology dissemination. In practice, they serve as the primary interface between farmers and government agencies, facilitating access to subsidized inputs, training programs, and information on improved farming practices. Through regular meetings and collective activities, FBOs are expected to promote knowledge sharing, reduce information asymmetry, and strengthen farmers' access to productive resources (Nuryanti & Swastika, 2016).

Conceptually, FBO participation may affect farm outcomes through several distinct mechanisms. For smallholder farmers, FBOs may function as effective learning centers (Fischer & Qaim, 2012; Kilpatrick et al., 2003) for accessing agricultural extension information (Michalek et al., 2018), while collective organization can lower transaction costs and facilitate access to key production inputs (Fischer & Qaim, 2012; Michalek et al., 2018; Nuryanti & Swastika, 2016). In addition, repeated peer interactions within farmer groups may enhance learning-by-doing and accelerate the diffusion of new technologies and practices. However, whether these mechanisms translate into measurable productivity gains depends critically on local institutional quality and group effectiveness (Francesconi & Wouterse, 2015).

Empirically, evidence on the impact of FBO participation remains inconclusive. Studies by Abdul-Rahaman and Abdulai (2018) in Northern Ghana, Michalek et al. (2018) in Slovakia, Abate et al. (2014) in Ethiopia, and Ainembabazi et al. (2017) in Africa reported significant positive effects of FBO participation on farm performance and farmers' livelihoods. Conversely, research by Bernard et al. (2008) in Senegal and Burkina Faso, Vandeplas (2013) in India, Addai et al. (2014) in Ghana, and Ofori et al. (2019) in Cambodia found that FBO membership had no significant impact on farm performance. These inconsistent findings may be attributed to regional differences, such as the characteristics of the FBOs per se, as well as methodological approaches (Abdul-Rahaman & Abdulai, 2018). Mojo et al. (2017) and Ofori et al. (2019) concur with this, suggesting that the impact of FBO membership is region- and commodity-specific, which warrants further investigation.

In Indonesia, research on the impact of FBO participation on farm performance is relatively scarce. Most existing studies focus on specific agricultural extension programs, such as farmer field schools, and their effects on farm performance (e.g. Feder et al., 2004; Haryanto et al., 2023; Luther et al., 2018; van den Berg et al., 2020). Among the limited studies addressing FBO participation, Rustinsyah (2019) employed a qualitative approach to examine the impact of beef cattle FBO membership, finding a positive effect on participants' livelihoods. Similarly, Ariningsih (2014), using a *t*-test, analyzed the impact of cooperative membership on income and found that cooperative members earned higher incomes than non-members.

However, it is imperative to note that Rustinsyah's (2019) qualitative study, which emphasizes process and context, may not be easily generalized (Yilmaz, 2013). Likewise, the use of a simple *t*-test in Ariningsih's (2014) study may suffer from systematic bias, as cooperative participation is often non-random, leading to differences between participants and non-participants (Haryanto et al., 2023). For example, farmers who are more educated, better informed, and more resourceful are more likely to join FBOs. Ignoring these systematic differences may lead to overestimation (Guo et al., 2015). Hence, existing evidence in Indonesia remains limited and methodologically constrained, particularly in identifying causal and context-dependent effects of FBO participation.

Given this context, the present study aims to assess the causal effect of FBO participation on maize productivity in Indonesia. This evaluation contributes to the literature in several ways. First, it enriches the discussion on how FBO participation affects farm performance in the context of Indonesia, built upon the premise put forward by Mojo et al. (2017) and Ofori et al. (2019), stating that the impact of such participation is context-dependent. This study also addresses the issue of generalization by providing the quantitative evidence. Second, the study employs the propensity score matching (PSM) method, a methodological advancement that constructs a comparable group of non-participants to address potential biases, allowing for a more robust analysis of the causal effects of FBO participation. While endogenous switching regression has been widely used to estimate treatment effects, it relies on valid instrumental variables, which are often difficult to identify. The use of invalid instruments may lead to biased estimates (Ma, Vatsa, et al., 2022). In contrast, PSM provides a more flexible and transparent framework for estimating causal effects in this context.

The remaining sections of this paper are organized as follows: Section 2 reviews the literature; Section 3 describes the data and empirical strategy; Section 4 presents the results and discussion; and Section 5 concludes the study.

2. Literature review

2.1. Farmer-based organization (FBO)

The terms 'farmer group', 'farmer association', 'farmer cooperative', and 'producer organization' are often used interchangeably in the agricultural literature to refer to farmer-based organizations. These organizations are owned and managed by their members to provide collective services and mutual benefits (Ahmed & Anang, 2019). These farmer-based organizations have been conceptually grouped into two categories: (1) community-based and resource-oriented organizations and (2) commodity-based and market-oriented organizations (Chamala & Shingi, 2007). The first category typically includes village-level cooperatives or associations that focus on addressing input-market challenges. These organizations provide production inputs such as seeds, fertilizers, information, and agricultural technologies. By purchasing inputs collectively, members can reduce the high costs that would otherwise be borne individually (Michalek et al., 2018). Participation in community-based and resource-oriented organizations can directly enhance farm production, as these organizations are typically small and localized (Chamala & Shingi, 2007).

The second type of organization typically focuses on a single agricultural commodity and market expansion. Specifically, these organizations aim to enhance farmers' bargaining power with upstream supply-chain players. By pooling agricultural outputs, farmers gain leverage in the market and secure better prices compared to trading individually (Chamala & Shingi, 2007; Michalek et al., 2018). As a result, membership can directly improve farmers' welfare. Additionally, farmers can also access agricultural product processing services that add value to their production outputs (Haldar & Damodaran, 2022). Another benefit is that these groups do not always require members to be in the same geographical area; instead, the common goal is to expand the market and collectively invest in agricultural processing equipment (Chamala & Shingi, 2007). Above all, some farmer groups may combine aspects of the two organization types mentioned above (Michalek et al., 2018).

2.2. Determinants of famer-based organization (FBO) participation

A decision to join an organization is often made using a cost-benefit analysis. In the case of farmer group participation, the benefits include improved access to input and output markets, such as agricultural technology and information, while the costs include membership fees and the time invested in activities. Each farmer perceives this cost-benefit tradeoff differently (Fischer & Qaim, 2012).

Abdul-Rahaman and Abdulai (2018) suggest that the decision to join an organization can be modeled as a binary choice influenced by observable socio-economic characteristics. According to their argument, human capital – proxied by education and experience – plays a key role in determining participation, as more educated and experienced farmers tend to be more open to knowledge development (Fischer & Qaim, 2012). Other factors that may influence the decision include economic and physical capital (Adjin et al., 2020; Boahene et al., 1999). For example, larger farm sizes and land ownership are associated with lower average fixed costs, which may increase the likelihood of participation. Similarly, households with higher income levels are more likely to participate in a framer group because they can afford agricultural inputs that are only accessible through group membership (Fischer & Qaim, 2012). Gender differences also play a role, with women showing lower participation rates due to higher opportunity costs, such as domestic responsibilities (Adjin et al., 2020; Charatsari et al., 2013).

2.3. The impact of farmer-based organization (FBO) on farm performance

A large body of empirical literature has examined the impact of FBO participation on farm performance. In general, many studies report positive effects of participation on productivity, technology adoption, and farm income. For example, S. Zhang et al. (2020) and Yang and Wang (2023) show that cooperative membership enhances technology adoption, particularly through training and knowledge dissemination. Similarly, Abdul-Rahaman and Abdulai (2018), Ma, Zheng, et al. (2022), and Taniu et al. (2024) find that participation improves farm income and financial performance, while Grashuis and Skevas (2023) and Neupane et al. (2022) document improvements in production efficiency and output.

Beyond productivity and income, FBOs have also been shown to influence broader aspects of farm and household behavior. For instance, participation may reduce production risks and variability (Ma, Zheng, et al., 2022), affect land use decisions such as cropland abandonment (Ma & Zhu, 2020), and shape labor allocation within households, including off-farm work participation (Zheng et al., 2023). These findings highlight the multifaceted roles of FBOs in rural development.

However, the empirical evidence is far from conclusive. Several studies report limited or insignificant effects of FBO participation. Bernard et al. (2008) and Ofori et al. (2019) find no significant impact on income or market participation, while Traore (2020) shows that inefficiencies within farmer organizations may even reduce productivity. Moreover, a recent meta-analysis by Ma, Hong, et al. (2023) suggests that the average effect of cooperative membership on yields is relatively small, with substantial variation across contexts. These mixed findings indicate that the effectiveness of FBOs is context specific (Mojo et al., 2017; Ofori et al., 2019). Differences in organizational quality, governance structures, and local institutional environments may influence whether participation translates into measurable productivity gains (Ma, Marini, et al., 2023). However, in the Indonesian context, existing evidence remains limited and methodologically constrained (e.g. Ariningsih, 2014; Rustinsyah, 2019), particularly in identifying causal and context-dependent effects of FBO participation. Based on the above discussion, this study tests the following hypothesis:

H1: Participation in farmer-based organizations (FBOs) has a positive effect on maize productivity in Indonesia.

3. Methodology

3.1. Data

This research uses data from the most current survey of the Indonesian Secondary Food Crops Cultivation Farm Holders Survey 2014 by Statistics Indonesia (BPS – *Badan Pusat Statistik*). This survey is a component of the Agricultural Census 2013, which is run every ten years. The survey presents nationally representative data of secondary crop commodities: maize, soybean, peanut, mung bean, cassava, and sweet potato. The data covers various aspects of farming households, including demographics,

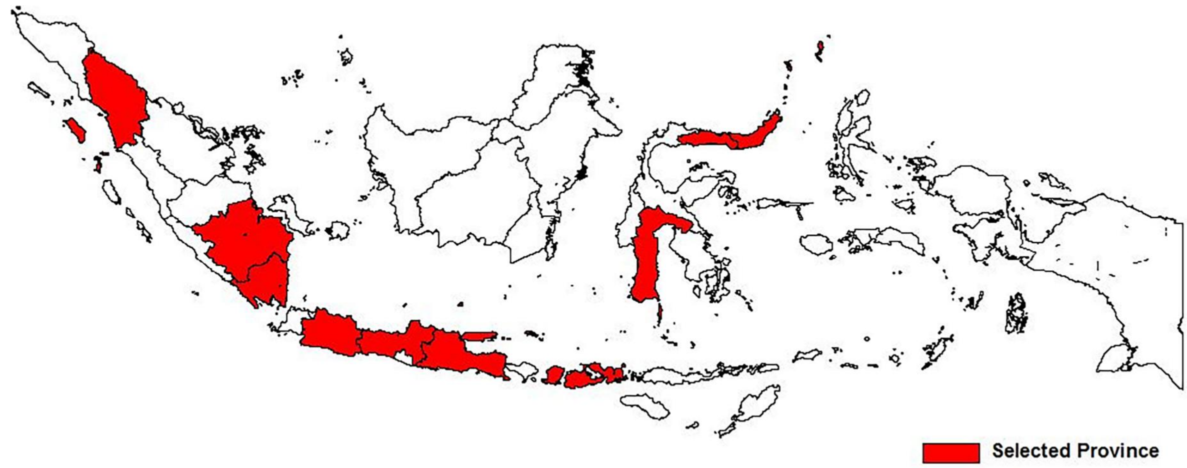

Figure 1. Distribution of samples.

general farming activities, recent crop information, production, cost structure, and assets such as buildings and facilities. The total sample of this study is 28,178 maize-farming households spread over ten major maize-farming provinces in Indonesia: North Sumatera, South Sumatera, Lampung, West Java, Central Java, East Java, West Nusa Tenggara, North Sulawesi, South Sulawesi, and Gorontalo. The distribution of the sample in this study is shown in Figure 1. While the dataset is from 2014, we argue that the analysis remains relevant to the current Indonesian context, as the structural characteristics of maize farming – such as the dominance of smallholder farmers, productivity trends, and farming practices – have remained relatively stable over the past decade.

3.2. Indonesian secondary food crops cultivation farm holders survey: sampling procedure

The data for this study were collected by Statistics Indonesia (BPS) using a structured questionnaire administered within ten major maize-farming provinces. The sampling process utilized two distinct sampling frames: the census block sampling frame and the household sampling frame. Census blocks were selected based on a list of ordinary and preparation census blocks that included households stratified by the type of secondary food crops cultivated in the previous year. To qualify as an eligible census block, a minimum of ten households meeting the eligibility criteria was required. The household sampling frame, in turn, was based on updated secondary crop production data for each selected census block, organized by the primary type of secondary crop.

A two-stage sampling method was employed for the survey. In the first stage, the probability proportional to size (PPS) method was used to select census blocks from the census block sampling frame. In the second stage, systematic random sampling was applied to select eligible farming households from the household sampling frame. A farming household was considered eligible if it had a minimum harvested area of 1,500 square meters (Statistics Indonesia, 2022).

3.3. Empirical strategy

This study aims to estimate the impact of FBO membership (*fbo_membership*) on farm productivity (*productivity*). The FBOs refer to farmer associations concerned with input access. Thus, this study seeks to measure the average treatment effect on the treated (ATT). Following the work of Abadie and Imbens (2016) and Abdia et al. (2017), the ATT is defined as below:

$$ATT = E\left[Y(1) - Y(0)|T = 1\right] \quad (1)$$

The notations Y (1) and Y (0) indicate outcome variables (*productivity*) if the maize farmer is a member or non-member of a farmer group, respectively. The term *T* shows the organization membership indicator where T = 1 denotes farmer group participation and 0 otherwise. Therefore, E [Y (1) |T = 1] is observable, while E [Y (0) |T = 1] is counterfactual. In other words, the same farmer cannot be a member and a non-member of a farmer group synchronously (Caliendo & Kopeinig, 2008; J. Zhang et al., 2021). The challenging task was to pick the control farmers (non-participating maize farmers) that would serve as a representative counterfactual. It is instructive to note that comparing the outcome variable between participating farmers (the treatment group) and non-participating farmers (the control group) might result in biased estimates (Baiyegunhi et al., 2019). A solution to this was to use propensity score matching (PSM), which can mimic the counterfactual. The underlying idea of PSM is to match the participating farmers with similar or identical non-participating farmers and then calculate the average difference in the outcomes between the two. Differencing the outcomes between identical participating and non-participating maize farmers can reduce the bias, yielding more reliable estimates (Baser, 2006).

The application of PSM in the analysis consists of two parts: (1) estimation of the propensity score of farmer group participation and (2) construction of a control group through matching. In the first stage, the propensity score is estimated as follows:

$$p(X) = \Pr[T = 1|X]; p(X) = F\{h(X_i)\} \tag{2}$$

The term $p(X)$ denotes a propensity score, *Pr* represents the likelihood of farmer group membership, T is the treatment status (1 indicates farmer group membership and 0 otherwise), given that X shows a vector of time-invariant observed characteristics. Based on the literature review, this research includes several socio-economic variables determining the probability of joining a farmer group. The term $F\{.\}$ denotes the probability distribution used in the model. This research uses the logistic distribution to estimate the propensity score.

In Equation (2), the dependent variable used is farmer group participation (*fbo_membership*). The independent variables include human capital which is represented by two variables: age (*age*) and years of education (*education*). Age is used as a proxy for farmers' experience. Following Fischer and Qaim (2012), this study also includes the square of age (*age_squared*) to capture a non-linear relationship, indicating that the probability of joining an organization may decline as farmers grow older. Demographic characteristics are captured by sex (*sex*).

Economic variables include farm size (*farm_size*), electricity access (*electricity*), land ownership status (*land_status*), and housing characteristics proxied by floor type (*floor*). Specifically, electricity access is categorized into no electricity, non-state electricity, and state electricity; land ownership status is classified as other ownership, rented, and self-owned land; while floor type includes soil, bamboo, wood, cement, tiles, and ceramic. Regional dummy variables (*province*) are also included to capture socio-economic differences across regions. All categorical variables are transformed into dummy variables, with one category omitted as the reference (base) group to avoid multicollinearity. The base categories are defined as follows: no electricity (*electricity),* soil (*floor*), other ownership (*land_status*), and East Java (*province*). The detailed coding, descriptions, and base categories of all categorical variables are provided in Appendix Table A1.

In the second stage of the analysis, a control group was constructed using a matching process based on the propensity score obtained from stage one. Various matching algorithms have been widely applied in the literature, i.e. one-to-one, k-nearest neighbors, Kernel-based, and radius matching. The selection of a matching algorithm was simple because, in large observations such as the current study, any matching algorithm would yield similar estimates (Caliendo & Kopeinig, 2008). This study uses nearest neighbors and Kernel-based matching. The nearest neighbor algorithm matches a particular treated farmer with the control farmer(s) who has the closest propensity score. The best matching results, i.e. balanced covariates, determine the total number of neighbors used in the analysis. Meanwhile, the Kernel-based algorithm matches a treated farmer with a weighted average of nearly all observations (Caliendo & Kopeinig, 2008). Two matching algorithms were employed to check the estimates' robustness (Baser, 2006).

After the matching process, the causal impact of farmer group membership could be determined by using the formula below:

$$ATT^{PSM} = E\left[Y(1)|T = 1, p(X) - E[Y(0)|T = 0, p(X)]\right] \tag{3}$$

The term $Y(1)$ shows the outcome variable (productivity defined by total production in tons divided by farm size in hectares or t/ha) of the participating maize farmers. Meanwhile, the term $Y(0)$ reveals the outcome variables of non-participating maize farmers. T indicates the membership status in binary values: 1 is for being a member and 0 for a non-member. The term $p(X)$ represents the matched propensity score.

3.4. Robustness test

While the employment of the Propensity Score Matching (PSM) as empirical strategy effectively addresses selection bias arising from observable characteristics, it does not account for potential bias due to unobserved factors. To assess the robustness of our estimates to hidden bias, this study utilized the Rosenbaum bounds sensitivity analysis. This approach evaluates how strongly an unobserved variable would need to influence selection into treatment to invalidate the estimated treatment effect (Haryanto, Wardana, Jamil, et al., 2023; Haryanto, Wardana, & Basconcillo, 2023; Taniu et al., 2024). Specifically, the sensitivity parameter (Γ) captures the extent to which unobserved factors may affect the odds of treatment assignment. Following Rosenbaum (2005), we identify a critical threshold value of Γ at which the estimated treatment effect becomes statistically insignificant. A higher Γ value indicates greater robustness to hidden bias, whereas a value close to one suggests that the results are sensitive to unobserved confounding.

In addition, we conduct an alternative robustness check using Ordinary Least Squares (OLS) regression applied to the matched sample. By restricting the estimation to the matched observations, this approach minimizes differences in observable characteristics between treated and control groups while allowing for further control of covariates in a regression framework. The OLS specification includes a comprehensive set of control variables capturing farmers' socio-economic characteristics, farm inputs, and regional factors. This complementary test enables us to assess whether the estimated association between FBO participation and productivity remains stable across specifications.

4. Result and discussions

4.1. Overview of maize production and use in Indonesia

Before presenting the empirical analysis, it is important to describe the broader trends in maize production and utilization in Indonesia. Figure 2 illustrates the evolution of maize supply (production) and demand (proxied by total domestic use) over the period 2016–2024. The figure shows that although

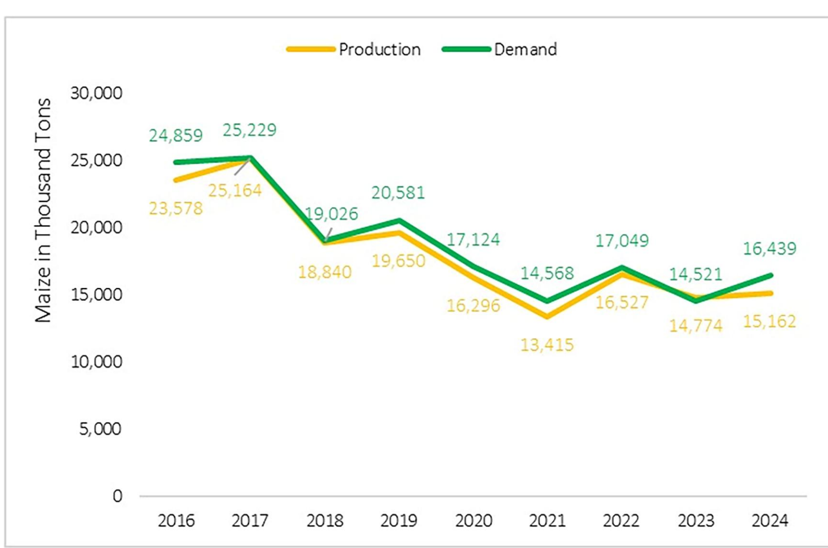

Figure 2. Trends in maize production (supply) and domestic use (demand) in Indonesia. *Source*: Ministry of Agriculture of Indonesia (various years).

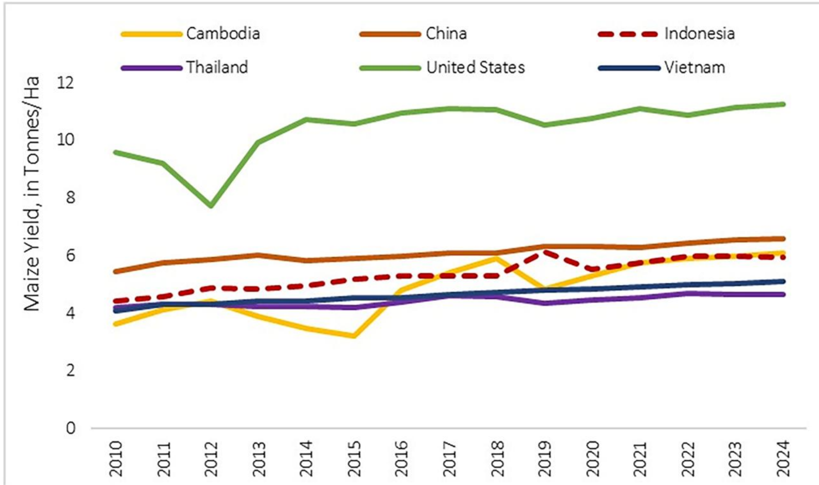

Figure 3. Trends in maize productivity of selected countries. *Source*: Hannah et al. (2026).

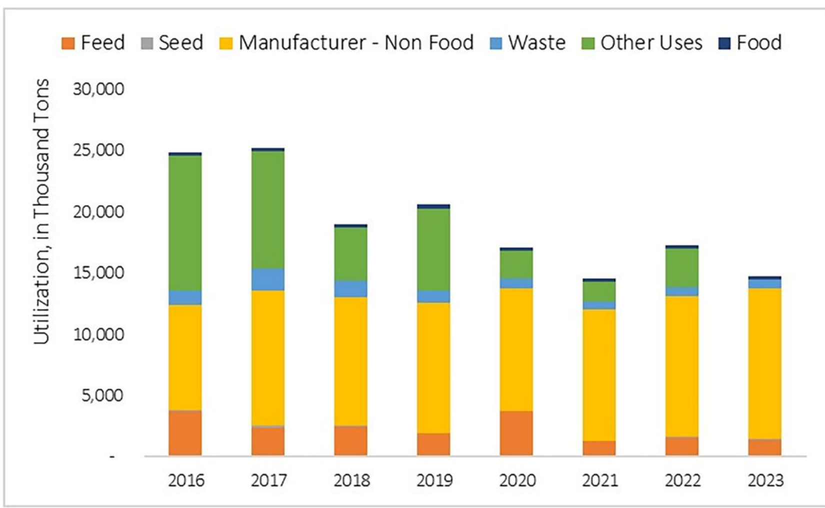

Figure 4. Composition of maize utilization in Indonesia by use category. *Source*: Ministry of Agriculture of Indonesia (various years).

maize production has fluctuated over time, it consistently remains below domestic demand, indicating a persistent supply gap. For instance, in 2024, maize production reached approximately 15.2 million tons, while demand stood at around 16.4 million tons. This imbalance suggests that domestic production has not fully kept pace with growing demand, thereby highlighting the importance of productivity-enhancing mechanisms in the maize sector.

In terms of productivity, Figure 3 compares maize productivity across selected countries from 2010 to 2024. Although Indonesia's productivity has improved over time, it remains below that of major producers such as the United States and China. While Indonesia performs similarly to Vietnam and slightly above Thailand in recent years, a substantial productivity gap persists. This highlights the potential for further productivity improvements in Indonesia's maize sector.

Additionally, Figure 4 further decomposes maize utilization by category, including feed, food consumption, manufacturing (non-food), seed, waste, and other uses. The figure indicates that a substantial share of maize is allocated for industrial and feed purposes, reflecting the increasing demand from the livestock and agro-processing sectors. In contrast, the proportion used for direct food consumption remains relatively smaller. This pattern underscores the strategic role of maize not only as a staple crop but also as a critical input in downstream industries.

4.2. Descriptive statistics of variables

The measurement and descriptive statistics of the variables used in the analysis are provided in Table 1. The data description is presented by FBO membership status. There were 14,394 farmers, or 51.08 percent of the total sample, participating in a farmer group (the treatment group). Around 13,784 farmers, or 48.92 percent, did not participate in a farmer group (the control group). Generally, the treatment group had higher maize production and productivity. The average production and productivity of the treatment group were 2.431 tons and 0.462 t/ha, respectively. Meanwhile, the average production and productivity of the control group were 2.170 tons and 0.440 t/ha, respectively. Furthermore, participating farmers also had a larger average farm size (0.548 ha) than non-participating farmers (0.527 ha). They also had a higher average education (5.883 years) than the non-members (5.291 years). In terms of age, participating farmers were older (50.122 years) than the non-members (48.991 years). Most farmers in both groups were male.

For categorical variables, values are reported using their numeric coding for descriptive purposes, while their distributions are interpreted based on category shares presented in Appendix Table A1. FBO members are more likely to have access to electricity from state providers, indicating relatively better infrastructure access compared to non-members. In contrast, the distribution of housing floor types is broadly similar across the two groups, as reflected by the statistically insignificant difference. With respect to land ownership status, FBO members exhibit a higher average value (1.511) than non-members (1.447), suggesting a greater prevalence of self-owned land among participating farmers. This indicates that farmers who join FBOs tend to have more secure land tenure. In general, the distribution of categorical variables suggests that FBO members are relatively better endowed in terms of productive assets and infrastructure.

4.3. Determinants of FBO participation

To address potential selection bias, we estimate the determinants of FBO participation using logistic regression. The results (Appendix Table A2) show that key factors such as age, education, farm size, gender, electricity access, floor type, and land ownership status significantly influence the likelihood of joining an FBO.

Participation probability increases with age until a certain point, after which it declines. More educated and male farmers, as well as those with larger farm sizes, are more likely to participate – consistent with previous findings by Fischer and Qaim (2012) and Kehinde (2021), which highlight socioeconomic and gender disparities in access to agricultural organizations. Electricity access and land ownership – used as proxies for wealth – also positively affect participation. Interestingly, farmers with soil flooring are more likely to join FBOs compared to those with higher-quality housing materials. Regional variation also exists, as indicated by the significant coefficients of province dummies relative to East Java.

4.4. The impact of FBO participation on productivity

The causal impact of FBO participation on maize productivity is estimated using propensity score matching (PSM), which compares farmers with similar observable characteristics across treatment and control groups. After confirming the common support condition (shown in Figure 5) and achieving covariate balance (shown by Table 2), the results from both the 7-nearest neighbor and kernel-based matching algorithms consistently indicate a positive and statistically significant impact of FBO participation on productivity.

Specifically, as shown in Table 3, the 1-nearest and 7-nearest neighbor estimations show that FBO membership increases maize productivity by 0.195 t/ha and 0.095 t/ha, respectively, corresponding to approximately a 2.2–4.4% increase relative to non-member farmers. Similarly, the kernel-based estimation suggests a productivity gain of 0.119 t/ha, equivalent to about a 2.7% improvement. These estimates are substantially larger than the naïve estimate, which is statistically insignificant, highlighting the

Table 1. Descriptive statistics.

Variables	Treatment group (*fbo_membership* = 1) $n = 14,394$				Control group (*fbo_membership* = 0) $n = 13,784$				
	Mean	SD	Min	Max	Mean	SD	Min	Max	*p*-value
productivity (tons/ha)	4.620	2.038	0.3	9	4.400	2.057	0.2	9	0.000***
production (tons)	2.431	3.201	0.048	176	2.171	2.483	0.02	42.5	0.000***
farm_size (ha)	0.548	0.616	0.02	28	0.527	0.537	0.03	10	0.002***
age (years)	50.122	11.802	15	90	48.991	12.15	14	90	0.000***
education (years)	5.883	4.107	0	18	5.291	4.161	0	18	0.000***
sex (0 = female; 1 = male)	0.919	0.272	0	1	0.884	0.32	0	1	0.000***
electricity (categorical: 0= no-electricity; 1= non-state; 2= state)	1.928	0.325	0	2	1.898	0.393	0	2	0.000***
floor (categorical: 0= soil; 1= bamboo; 2= wood; 3= cement; 4 = tiles; 5 = ceramic)	3.073	1.649	0	5	3.072	1.572	0	5	0.986
land_status (categorical: 0= other ownership; 1= rented; 2= self-owned)	1.511	0.773	0	2	1.447	0.812	0	2	0.000***

Note: p-value indicates statistical mean differences between treatment and control group (unmatched sample). $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

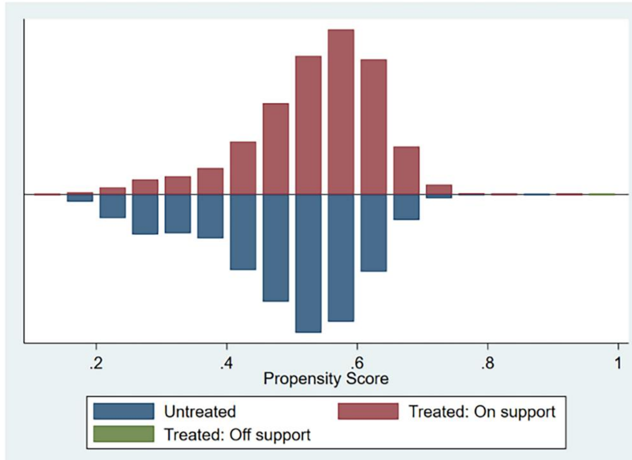

Figure 5. Distribution of propensity scores.

Table 2. After the matching quality test.

Variables	Mean		*p*-Value
	Treatment group	Control group	
age	50.122	50.018	0.454
education	5.883	5.812	0.143
farm_size	0.546	0.536	0.123
sex	0.919	0.920	0.973
electricity	1.928	1.927	0.769
floor	3.073	3.070	0.900
land_status	1.511	1.507	0.629

Note: p-value indicates statistical mean differences between treatment and control group (matched sample based on 7-nearest neighbor). ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table 3. The impact of farmer group participation on productivity.

Matching algorithm	Coefficient (ATT)
Naïve	0.042
	(0.033)
1-NN	0.195***
	(0.025)
7-NN	0.095***
	(0.027)
Kernel	0.119***
	(0.025)

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

importance of addressing selection bias in evaluating the impact of collective participation. Overall, these findings suggest that farmer group participation contributes positively to farm performance.

Despite being statistically significant, the magnitude of the estimated effect of FBO participation is economically modest. It means that while FBO participation contributes to improving farm performance, it does not represent a transformative productivity gain. Instead, the findings indicate that FBOs function more as incremental support mechanisms rather than primary drivers of productivity growth. This distinction is crucial, as it highlights that participation alone may not be sufficient to generate large productivity gains without complementary improvements in other production factors.

These findings are broadly consistent with the existing literature emphasizing the role of collective action in improving agricultural outcomes. Previous studies have shown that farmer-based organizations enhance access to inputs, facilitate knowledge sharing, and improve bargaining power, all of which contribute to higher productivity and income (Abdul-Rahaman & Abdulai, 2018; Fischer & Qaim, 2014; Liu et al.,2019; Ma, Vatsa, et al., 2022; Ma & Abdulai, 2016). In the Indonesian context, this study further highlights the relevance of FBO participation in the maize sector. By employing a quantitative approach with nationally representative data, the findings complement earlier studies by Rustinsyah (2019) and Ariningsih (2014), which document the benefits of FBO participation for smallholder farmers. In this regard, the findings contribute to the literature by providing more robust and nationally representative evidence, thereby strengthening the empirical understanding of the impact of FBO participation on farm performance in Indonesia. More broadly, the finding also supports the argument presented in the literature that FBOs serve as platforms for knowledge sharing, collective input procurement, and improved bargaining power (Chamala & Shingi, 2007; Michalek et al., 2018; Yang & Wang, 2023). At the same time, the relatively modest effect observed in this study aligns with a growing body of evidence suggesting that the impact of farmer organizations is heterogeneous and context dependent (Mojo et al., 2017; Ofori et al.,2019). In several settings, cooperative participation has been found to have limited or even insignificant effects, particularly when organizational capacity is weak or when participation is largely administrative rather than functional (Bernard et al.,2008; Ma, Marini, et al., 2023; Ofori et al.,2019).

Furthermore, the effectiveness of FBOs is closely linked to the broader institutional environment, particularly the quality of agricultural extension services and local governance capacity. Extension agents play a critical role in translating knowledge and technology into farm-level practices, and their interaction with farmer groups determines the extent to which collective action translates into productivity gains. In regions where extension services are more active and better resourced, farmer groups are more likely to function as effective platforms for learning, coordination, and technology adoption. In contrast, in areas with limited institutional support, the benefits of FBO participation are likely to be weaker.

In the Indonesian context, the governance of agricultural extension has evolved under a decentralized framework following the implementation of *Undang-Undang* (UU) No. 23 of 2014, which devolved responsibilities to provincial and district governments (Arifin, 2024). While this study is based on data prior to this reform, the current institutional setting provides important context for interpreting the findings. Decentralization allows policies and extension services to be more responsive to local conditions, but it also introduces substantial variation in implementation capacity across regions. Differences in local fiscal resources, administrative capability, and policy priorities may lead to unequal provision of extension services and support for farmer organizations. In this regard, the modest effects observed in this study may become even more pronounced under the decentralized system, where the effectiveness of farmer-based organizations is likely to depend more strongly on local institutional capacity.

At the regional level, participation in farmer groups varies considerably, reflecting differences in local conditions. Although the national participation rate reached 61.95% in 2024, a substantial proportion of farmers (approximately 38%) remain outside farmer groups. In several provinces, particularly in eastern Indonesia, participation rates are significantly below the national average. For instance, farmer group participation in Maluku and North Maluku was 5.76% and 18.58%, respectively (Statistics Indonesia, 2024). Beyond institutional support such as extension services, disparities in participation represent an additional challenge in enhancing the effectiveness of farmer-based organizations, particularly in regions where participation remains low.

4.5. Robustness test and heterogeneous effects

To verify the reliability of our findings, we conducted a robustness check using two alternative approaches: Rosenbaum test and an Ordinary Least Squares (OLS) regression for the matched sample. Table 4 reports the result of the Rosenbaum bounds sensitivity analysis for different matching algorithms.

The findings indicate that the estimated treatment effects are statistically significant at $\Gamma = 1$ across all specifications, confirming the baseline results obtained from the PSM estimation. However, as Γ increases, the *p*-values rise rapidly, and the statistical significance of the estimates diminishes. Specifically, for the NN-1 matching algorithm, the results remain statistically significant up to approximately $\Gamma = 1.13$ but become insignificant at $\Gamma = 1.14$. In contrast, the NN-7 and Kernel matching results lose statistical significance at lower levels of Γ, around 1.04 and 1.07, respectively. These results suggest that the estimated impact of FBO participation on maize productivity is somewhat sensitive to hidden bias. Therefore, while the PSM results provide evidence of a positive impact of FBO participation and maize productivity, the sensitivity analysis highlights the need for cautious interpretation, as unobserved heterogeneity may still play a role.

Furthermore, the OLS regression for the matched sample allows us to examine whether the positive association between FBO membership and productivity remains consistent after controlling for relevant covariates. The results, as presented in Table 5, confirm the robustness of our estimates. Specifically, FBO

Table 4. Rosenbaum test for various matching algorithms.

	p-Value		
Γ	NN-1	NN7	Kernel
1.00	0.0000	0.0003	0.0000
1.01	0.0000	0.0018	0.0000
1.02	0.0000	0.0084	0.0000
1.03	0.0000	0.0297	0.0003
1.04	0.0000	0.0834	0.0015
1.05	0.0000	0.1878	0.0066
1.06	0.0000	0.3469	0.0233
1.07	0.0000	0.5374	0.0666
1.08	0.0000	0.7180	0.1541
1.09	0.0002	0.8544	0.2943
1.10	0.0010	0.9369	0.4733
1.11	0.0042	0.9772	0.6564
1.12	0.0147	0.9932	0.8073
1.13	0.0420	0.9983	0.9081
1.14	0.1001	0.9996	0.9630
1.15	0.2010	0.9999	0.9874

Table 5. OLS regression of the impact of FBO on productivity for matched sample.

	Matched sample	
Variables	(1)	(2)
fbo_membership	0.168***	0.089***
	(0.024)	(0.023)
age	0.006	0.005
	(0.007)	(0.007)
age_squared	−0.000	−0.000
	(0.000)	(0.000)
education	0.041***	0.031***
	(0.003)	(0.003)
farm_size	−0.428***	−0.281***
	(0.024)	(0.025)
sex	−0.061	0.036
	(0.041)	(0.039)
i.electricity		
non-state	−0.008	−0.070
	(0.098)	(0.094)
state	0.066	−0.128*
	(0.078)	(0.076)
i.floor		
bamboo	−0.141	0.044
	(0.143)	(0.138)
wood	0.031	0.342***
	(0.046)	(0.052)
cement	0.345***	0.373***
	(0.039)	(0.040)
tiles	0.322***	0.434***
	(0.056)	(0.054)
ceramic	0.549***	0.426***
	(0.041)	(0.040)
i.land_status		
rented	0.409***	0.266***
	(0.043)	(0.041)
self-owned	0.249***	0.156***
	(0.032)	(0.031)
constant	3.633***	4.590***
	(0.191)	(0.185)
province	No	Yes
Observations	27,568	27,568
R-squared	0.040	0.132

Note: Standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. The regression of the matched sample is based on 1-NN Matching.

membership continues to exhibit a positive and statistically significant impact on farmers' productivity across specifications. In column (1), without regional controls, FBO participation increases productivity by 0.168, while in column (2), after including regional dummy variables, the effect remains positive and significant (0.089). These findings suggest that the productivity advantage associated with FBO participation

Table 6. The heterogeneous effects of FBO participation on productivity.

Categorical variables	Treatment group	Control group	ATT
By sex			
Female	4.671	4.454	0.217***
	(0.0598)	(0.0525)	(0.0799)
Male	4.588	4.393	0.195***
	(0.0181)	(0.0186)	(0.0259)
By land ownership			
Other ownership	4.290	4.150	0.140**
	(0.0393)	(0.0395)	(0.0560)
Rented	4.777	4.554	0.223***
	(0.0468)	(0.0478)	(0.0668)
Self-owned	4.638	4.446	0.192***
	(0.0211)	(0.0213)	(0.0300)

Note: Standard errors in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. The table based on 1-NN Matching.

is not driven by regional or demographic heterogeneity. The consistency of the results across specifications provides additional support for the stability of the estimates within the matched sample. Hence, the results from Rosenbaum and OLS regression with matched sample indicate that the positive association between FBO participation and productivity is robust across specifications but remains sensitive to potential hidden bias.

To further understand the heterogenous effects, we disaggregate the analysis by gender and land ownership status. The results are presented in Table 6. In general, FBO participation significantly increases productivity across all categories, suggesting that the benefits of collective action are broadly shared among farmers. However, the magnitude of the effect varies across subgroups. The productivity gains are more pronounced for female farmers (ATT = 0.217) compared to their male counterparts (ATT = 0.195), implying that FBOs play a particularly important role in supporting women farmers.

Similarly, when disaggregated by land ownership, FBO participation has the largest impact on farmers cultivating rented land (ATT = 0.223), followed by those with self-owned land (ATT = 0.192). This suggests that FBOs are especially effective in enhancing productivity among tenant farmers, who often face greater production constraints and resource limitations. The finding underscores the potential of FBOs to reduce inequality in agricultural performance by improving inclusivity and access to collective resources for less advantaged groups.

5. Conclusion and policy implications

This study investigates the impact of FBO membership on maize productivity using the most recent dataset of maize farmer households in Indonesia. This study hypothesizes that FBO participation improves maize productivity. Using the PSM method, this study offers several contributions to the literature. This study enriches the discussion on how FBO participation influences farm performance in Indonesia, emphasizing the context-dependence noted in prior research. Employing the PSM method, this study addresses biases by constructing a comparable group of non-participants, enabling a more robust analysis of causal effects. Compared to the widely used endogenous switching regression model, which relies on valid instrumental variables that can be difficult to identify, PSM offers greater flexibility and reduces the risk of biased estimates. The PSM analysis indicated that FBO participation increases maize productivity by approximately 0.095 to 0.195 t/ha or approximately 2.2% to 4.4% compared to non-member farmers. It implies that the roles of FBOs remain relevant in maize productivity in Indonesia.

The findings of this study provide several important implications for agricultural policy, particularly in the design and implementation of farmer-based organization (FBO) programs. While the results indicate that FBO participation has a positive and statistically significant effect on maize productivity, the magnitude of the impact is relatively modest. Although these gains are small at the individual farm level, they may translate into meaningful aggregate improvements in national maize production if participation rates increase, given approximately 38% of maize farmers are not currently affiliated with FBOs.

However, the modest magnitude of the estimated impact suggests that expanding FBO participation alone is unlikely to generate substantial productivity gains without complementary improvements in institutional quality. Therefore, policy efforts should shift from a purely expansion-oriented approach toward strengthening the effectiveness of existing farmer organizations. Particularly, improving internal governance such as leadership quality, transparency, accountability, and active member participation is critical to ensuring that FBOs function as effective platforms for coordination, knowledge sharing, and innovation.

In this regard, different institutional actors play complementary roles. At the national level, the Ministry of Agriculture should focus on enhancing the design of FBO-based programs by developing standardized capacity-building modules that target organizational management, financial transparency, and collective decision-making. These programs should move beyond input distribution and emphasize strengthening the functional role of FBOs as economic and learning institutions. At the subnational level, districts are responsible for the implementation of extension services and should prioritize improving the quality and intensity of field-level support. Strengthening the capacity and incentives of agricultural extension agents is particularly important, as their interaction with farmer groups determines whether knowledge dissemination translates into actual productivity gains.

Furthermore, village governments can play a strategic supporting role through the allocation of *Dana Desa* (Village Fund). These resources can be directed toward strengthening farmer group activities, including training programs, collective input procurement, and small-scale agricultural infrastructure. However, such interventions should be carefully designed to encourage active participation and local ownership, rather than reinforcing dependence on government assistance. Importantly, the sustainability of FBOs depends on their ability to operate beyond their function as administrative channels for government programs. Therefore, policies should promote a more bottom-up approach to FBO development, where group formation and strengthening are driven by farmers' needs, economic incentives, and local conditions. This includes encouraging regular group interactions, fostering market-oriented activities, and enhancing linkages between farmer groups and value chains.

Finally, given the substantial variation in FBO participation and effectiveness across regions, policy interventions should be spatially targeted. Regions with low participation rates and weaker institutional capacity should receive greater attention, particularly in terms of extension service provision and institutional strengthening. In this context, improving agricultural productivity requires not only expanding access to farmer organizations but also strengthening the broader governance structures that determine their effectiveness.

Future research will benefit from utilizing more recent nationally representative datasets and including other agricultural commodities in the analysis. In the context of Indonesia, the latest nationally representative agricultural survey conducted in 2024 is likely to offer a valuable resource. Additionally, methodological advancements could focus on identifying causal relationship by using natural experiment or valid instrumental variable.

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Data availability statement

The data that support the findings of this study are available from the authors upon reasonable request. Access to the data may be subject to restrictions due to confidentiality and data-sharing agreements.

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Appendix A

Table A1. Categorical variables' sample definition and distribution.

				Treatment group (fbo_membership = 1) $n = 14{,}394$		Control group (fbo_membership = 0) $n = 13{,}784$	
Variables	Code	Base category	Description	*n* (sample)	% (freq)	*n* (sample)	% (freq)
electricity	0 = No electricity	Yes	Household has no electricity access	282	1.96%	429	3.11%
	1 = non-state		Electricity from private/non-state source	468	3.25%	554	4.02%
	2 = state		Electricity from state provider	13,644	94.79%	12,801	92.87%
floor	0 = soil	Yes	Lowest housing quality	2,156	14.98%	1,687	12.24%
	1 = bamboo		Semi-permanent flooring	75	0.52%	134	0.97%
	2 = wood		Wooden flooring	1,829	12.71%	2,241	16.26%
	3 = cement		Permanent flooring	4,939	34.31%	4,948	35.90%
	4 = tiles		Higher-quality flooring	1,296	9.00%	980	7.11%
	5 = ceramic		Highest-quality flooring	4,099	28.48%	3,794	27.52%
land_status	0 = other ownership	Yes	Informal or unspecified ownership	2,504	17.40%	2,842	20.62%
	1 = rented		Land is rented	2,025	14.07%	1,933	14.02%
	2 = self-owned		Land is owned by farmer	9,865	68.54%	9,009	65.36%
provinces	0 = East Java	Yes	Farmers living in East Java	4,662	32.4%	3,477	25.2%
	1 = South Sulawesi		Farmers living in South Sulawesi	1,580	11.0%	1,780	12.9%
	2 = West Nusa Tenggara		Farmers living in West Nusa Tenggara	816	5.7%	840	6.1%
	3 = Lampung		Farmers living in Lampung	1,234	8.6%	843	6.1%
	4 = Central Java		Farmers living in Central Java	3,029	21.0%	2,378	17.3%
	5 = Gorontalo		Farmers living in Gorontalo	827	5.7%	989	7.2%
	6 = North Sumatera		Farmers living in North Sumatera	1,062	7.4%	1,248	9.1%
	7 = South Sumatera		Farmers living in South Sumatera	498	3.5%	422	3.1%
	8 = West Java		Farmers living in West Java	496	3.4%	1,272	9.2%
	9 = North Sulawesi		Farmers living in North Sulawesi	190	1.3%	535	3.9%

Table A2. Determinants of FBO participation.

Variable	Coefficient	Marginal effect (dy/dx)
age	0.0442***	0.0105***
	(0.007)	(0.002)
age_squared	−0.000***	−7.33e-05***
	(6.75e-05)	(1.60e-05)
education	0.0516***	0.0123***
	(0.003)	(0.001)
farm_size	0.169***	0.0400***
	(0.026)	(0.006)
sex	0.351***	0.0833***
	(0.042)	(0.010)
i.electricity		
non-state	0.183*	0.0434*
	(0.102)	(0.0240)
state	0.300***	0.0711***
	(0.0827)	(0.0195)
i.floor		
bamboo	−0.317**	−0.0755**
	(0.154)	(0.0366)
wood	−0.222***	−0.0527***
	(0.0559)	(0.0133)
cement	−0.181***	−0.0430***
	(0.0424)	(0.0100)
tiles	0.0823	0.0193
	(0.0560)	(0.0132)
ceramic	−0.196***	−0.0465***
	(0.0421)	(0.00998)
i.land_status		
rented	0.153***	0.0365***
	(0.0437)	(0.0104)
self-owned	0.135***	0.0322***
	(0.0328)	(0.00780)
Constant	−2.069***	
	(0.199)	
provinces	YES	YES
Observations	28,178	28,178

Note: Standard errors in parentheses, $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table A3. Determinants of FBO participation (full regression result).

Variables	Coefficient	Marginal effect (dy/dx)
age	0.0442***	0.0105***
	(0.007)	(0.002)
age_squared	−0.000***	−7.33e-05***
	(6.75e-05)	(1.60e-05)
education	0.0516***	0.0123***
	(0.003)	(0.001)
farm_size	0.169***	0.0400***
	(0.026)	(0.006)
sex	0.351***	0.0833***
	(0.042)	(0.010)
i.electricity		
non-state	0.183*	0.0434*
	(0.102)	(0.0240)
state	0.300***	0.0711***
	(0.0827)	(0.0195)
i.floor		
bamboo	−0.317**	−0.0755**
	(0.154)	(0.0366)
wood	−0.222***	−0.0527***
	(0.0559)	(0.0133)
cement	−0.181***	−0.0430***
	(0.0424)	(0.0100)
tiles	0.0823	0.0193
	(0.0560)	(0.0132)
ceramic	−0.196***	−0.0465***
	(0.0421)	(0.00998)
i.land_status		
rented	0.153***	0.0365***
	(0.0437)	(0.0104)
self-owned	0.135***	0.0322***

(*continued*)

Table A3. Continued.

Variables	Coefficient	Marginal effect (dy/dx)
	(0.0328)	(0.00780)
i.province		
South Sulawesi	−0.288***	−0.0701***
	(0.053)	(0.0130)
West Nusa Tenggara	−0.267***	−0.0651***
	(0.061)	(0.0148)
Lampung	0.0803	0.0192
	(0.053)	(0.0127)
Central Java	−0.0355	−0.00856
	(0.036)	(0.00873)
Gorontalo	−0.341***	−0.0830***
	(0.061)	(0.0149)
North Sumatera	−0.497***	−0.121***
	(0.052)	(0.0126)
South Sumatera	−0.115	−0.0279
	(0.075)	(0.0182)
West Java	−1.203***	−0.280***
	(0.059)	(0.0123)
North Sulawesi	−1.448***	−0.326***
	(0.0907)	(0.0168)
Constant	−2.069***	
	(0.199)	
Observations	28,178	28,178

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

Table A4. Full results of robustness check of OLS regression for matched sample.

	Matched sample	
Variables	(1)	(2)
fbo_membership	0.168***	0.089***
	(0.024)	(0.023)
age	0.006	0.005
	(0.007)	(0.007)
age_squared	−0.000	−0.000
	(0.000)	(0.000)
education	0.041***	0.031***
	(0.003)	(0.003)
farm_size	−0.428***	−0.281***
	(0.024)	(0.025)
sex	−0.061	0.036
	(0.041)	(0.039)
i.electricity		
non-state	−0.008	−0.070
	(0.098)	(0.094)
state	0.066	−0.128*
	(0.078)	(0.076)
i.floor		
bamboo	−0.141	0.044
	(0.143)	(0.138)
wood	0.031	0.342***
	(0.046)	(0.052)
cement	0.345***	0.373***
	(0.039)	(0.040)
tiles	0.322***	0.434***
	(0.056)	(0.054)
ceramic	0.549***	0.426***
	(0.041)	(0.040)
i.land_status		
rented	0.409***	0.266***
	(0.043)	(0.041)
self-owned	0.249***	0.156***
	(0.032)	(0.031)
South Sulawesi		−1.238***
		(0.050)
West Nusa Tenggara		−0.443***
		(0.057)
Lampung		−0.209***
		(0.051)

(*continued*)

Table A4. Continued.

	Matched sample	
Variables	(1)	(2)
Central Java		−1.224***
		(0.034)
Gorontalo		−1.610***
		(0.057)
North Sumatera		−0.230***
		(0.049)
South Sumatera		−0.672***
		(0.071)
West Java		−0.711***
		(0.052)
North Sulawesi		−2.682***
		(0.077)
Constant	3.633***	4.590***
	(0.191)	(0.185)
Observations	27,568	27,568
R-squared	0.040	0.132

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