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Impact of Farmer Associations on Sales and Crop Diversification

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ABSTRACT

Contributing to the growing interest in understanding the impact of farmer cooperatives on rural household welfare, we add new empirical evidence to the current literature and debate. In particular, this study investigates the impact of farmer cooperatives on sales per hectare of land and crop diversification, which have been largely overlooked. We apply the Propensity Score Matching method to the Cambodia Inter-Censal Agricultural Survey 2019, with its large sample size of 16,000 small-scale producers. Additionally, we perform a robustness check to ensure our findings are unbiased. Results indicate that Cambodian farmers perceive the cooperatives as a risk-sharing mechanism or knowledge-sharing platform that provides technical know-how to cope with natural calamities. Propensity Score Matching (PSM) outputs show a significantly positive impact of participating in the cooperatives on sales and the crop diversification index. This study thus advocates increasing technical support and implementing policies by the government to help cooperatives thrive and expand.

Keywords: Agriculture, Cambodia, crop, farmer association, impact

INTRODUCTION

The growth of farmers' organisations has been remarkable in many parts of the world, especially in imperfect markets (Candemir et al., 2021). In 2015, the European continent had over 51,000 farmer associations with a turnover of approximately USD 415 billion (Grashuis & Su, 2019). Additionally, the United States had 1,871 organisations with more than two million members. Due to its considerable importance, the concept of farmers' associations has drawn much attention from scholars and the governments of developing countries

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(Abebaw & Haile, 2013). However, despite increasing empirical evidence, their impact is unclear (Bizikova et al., 2020). Theoretically, farmer organisations improve agricultural smallholders' profit, income, and productivity by increasing their collective bargaining power, improving product quality and access to farming knowledge and technologies, minimising logistic and marketing costs due to economies of scale, and reducing information asymmetry (Ito et al., 2012). Therefore, such an institutional arrangement is deemed a consequential route out of poverty for small-scale producers.

Many studies have proven such a claim. For instance, Bernard et al. (2008) and Wollni and Zeller (2007) show that joining a farmer cooperative leads to a significant increase in price received and agricultural profit. Likewise, a study in Nigeria suggests higher technical efficiency among cooperative members than those who do not join any organisation (Olagunju et al., 2021). In Kenya, members of agricultural cooperatives sell bananas for a price of 23% higher than non-members (Fischer & Qaim, 2012). Other empirical studies also document the strong and positive influence of participation in farmer associations on other indicators of member performance, such as fertiliser and pesticide adoption (Abebaw & Haile, 2013), rising yields, and household income (Ma & Abdulai, 2016), and the reduction of cropland abandonment (Ma & Zhu, 2020). Furthermore, agricultural cooperatives improve technology choices, information sharing, and access to banking and credit systems for smallholder farmers in Cambodia (Ofori et al., 2019).

Nevertheless, there are also cases where cooperatives do not necessarily improve farmers' conditions or, at worst, have an adverse effect. In particular, Malvido Perez Carletti et al.(2018) found no benefits in joining a farmer's organisation. On the contrary, they observe farmer cooperatives' negative impact on the wine price in Argentina. Similarly, an empirical study from the Austrian wine market indicates that members of cooperatives have a high tendency to free-ride on quality. Consequently, wines produced by the cooperatives generally have considerably lower quality on average (Pennerstorfer & Weiss, 2013). In Ethiopia, Chagwiza et al. (2016) found no significant impact of cooperative membership on the price of milk and butter, although they assert that such membership facilitates technological transformation. Barrett (2008) also claims that while farmer associations significantly impact high-value crops, there is little evidence to prove this statement is true for staple food grains.

With that said, the research studies mentioned above also have limitations. Therefore, their findings should be interpreted with caution. For example, Chagwiza et al. (2016) use quantitative data from only 400 samples. Many other studies also rely only on small sample sizes, even though most of them use a popular econometric method called Propensity Score Matching (PSM), which requires a dataset with a large sample size to improve its matching mechanism and accuracy (Ito et al., 2012; Ma & Abdulai, 2016).

Furthermore, Ainembabazi et al. (2017) assume the decision to participate in the farmer association is random. However, such an assumption is unlikely because participation can be driven by education, knowledge, ability, or motivation to improve household income (Candemir et al., 2021). Such limitations may be another reason for the mixed evidence in the current body of literature.

This study provides empirical evidence to the growing literature on the role of farmer association by estimating its impact on farming households. We use one developing country, Cambodia, as our case study, and the decision is based on several reasons. Firstly, much previous research has been conducted in the context of Africa and India. Very little evidence can be found in the least developed countries in Asia in general, and in Cambodia in particular, where they grow one of the highest quality rice in the world (Bizikova et al., 2020; Theng et al., 2014). Secondly, unlike in many other countries, especially in the Global North, where cooperatives are highly autonomous, farmer associations in Cambodia depend largely on funding from NGOs, and they tend to collapse once the funding is exhausted. Thus, the context differs from those previously studied, making it fascinating to understand different cooperatives.

Results indicate that poorer households and those who have experienced or frequently faced natural disasters are significantly more likely to join a farmer cooperative than those who are less likely to face such challenges. These findings suggest that poor rural farmers in Cambodia use cooperatives as a risk-sharing mechanism or an agricultural knowledge-sharing platform that teaches them how to deal with environmental calamities. PSM outputs also show a significant effect of joining an agricultural organisation on crop sales per hectare of plant area and crop diversification. For sales, the positive effects range from 11.7% to 15.7%. At the same time, for crop diversification, member households are found to be 3.3% more likely to adopt commercial crops, including aromatic rice, mango, banana, cassava, or cashew nuts, for plantation. This effect is also significant at the 1% level.

The contribution of this study is threefold. First, while previous literature concentrates on understanding whether participating in cooperatives influences farmers' income or profit—factors influenced by production costs and current market prices of commodities—we shift the focus to sales per hectare of land and crop diversification. These indicators are often overlooked (Bizikova et al., 2020) despite diversification being reported as crucial for farm sustainability (Booth & Golooba-Mutebi, 2014). Secondly, most research in Asia or developing countries uses only a few hundred samples, whereas we employ a nationally representative dataset of approximately 16,000 household samples. It enables us to improve the accuracy of our estimations and meet the essential requirements of PSM. Thirdly, previous literature has focused on specific commodities such as bananas (Fischer

& Qaim, 2012), apples (Ma & Abdulai, 2016), and coffee (Wollni & Zeller, 2007). In contrast, we study multiple valuable agro-industry crops, including aromatic rice, mango, banana, cashew nut, and cassava. It is noteworthy that rice is a staple in the everyday diet of much of the Southeast Asian population, making this research study relevant to food security. To the best of our knowledge, no studies have used nationally representative data on the impact of farmer associations on agricultural sales and crop diversification in Southeast Asia.

This study also aligns well with the special issue theme in several ways. Firstly, it focuses on farmer associations, foundational to ensuring global food production's sustainability, food security, and resilience. In addition, farmer associations have the potential to enhance climate change adaptation. By examining their impacts, this study provides valuable insights into how to strengthen and support these vital components of human civilisation. Secondly, emphasising empirical evidence is highly aligned with conducting impactful scientific research. Grounding the analysis in rigorous data and quantitative methods allows the study to provide robust, evidence-based conclusions that inform policy and practice. This type of rigorous, scientifically driven research is essential for fostering the preservation of high civilisations, as it allows for developing effective, data-driven interventions and solutions. Finally, the study's focus on the role of farmer associations directly addresses the research theme. These institutions are inherently human-centric, as they exist to support and empower agricultural communities, many of which are a crucial part of Southeast Asian countries. By understanding their impacts, the study provides insights into how humans organise and collaborate to tackle shared challenges. It aligns with the broader goal of understanding humanity and using that knowledge to drive positive social change.

LITERATURE REVIEW

Many academics argue that farmer cooperatives are an effective solution to address agricultural challenges in developing nations. This idea is grounded in the induced innovation theory (Rogers, 2003), which suggests that farmer associations or cooperatives, due to their close relationships with individual farmers, are the most effective mechanisms for enhancing agricultural technology and meeting the needs of farmers. These associations commonly provide services such as technological training and encourage members to transition from traditional farming methods to modern practices and technologies. In some instances, associations also offer assistance in the form of crop and livestock production inputs. While contracting companies or supporting agencies may be involved in training programs, the members of these associations generally have greater access to resources such as fertiliser, new seeds, markets, knowledge, and machinery compared to non-organised farmers. Consequently, this increased access motivates organised and non-organised farmers to form or join associations.

By coming together as a group and pooling their resources, individual farmers can benefit by sharing production costs and expanding their investments. It allows them to use economies of scale, resulting in significant advantages. Using Ostrom's (2009) socio-ecological system framework, Zhu and Wang (2024) assert that Chinese farmers in the Tarim River Basin who participate in cooperatives are more likely to adopt water-saving irrigation technology, which in turn tends to reduce the water shortage problem in the area. Additionally, farmers' associations have been recognised as important catalysts for the commercialisation of farming, connecting smallholders with agri-businesses (Reardon et al., 2019). For example, smallholder farmers who join a cooperative can collectively sell their products to agro-processors, offering greater convenience for buyers and exporters compared to non-organised farmers. Farmer associations play a crucial role in facilitating business transactions between farmers and potential buyers or companies, exemplified by Kenya, Ethiopia, and Zambia exporting their green beans to Europe (Fischer & Qaim, 2012). Furthermore, farming cooperatives serve as a risk-sharing mechanism, providing insurance against crop failure and a knowledge-sharing platform for disseminating best practices and minimising or preventing disaster impacts. Moreover, a cooperative, acting as a small-scale producer's cartel, can exert more control over the market and prices, thereby improving its position and bargaining power.

However, it should be highlighted that cartels typically do not last long because every member has an incentive to oversupply. Cheating members can reap the benefits of additional sales without bearing the full costs of driving prices down, which all members share. In other words, each member has an incentive to raise their profits at the expense of others. Moreover, large organisations face additional institutional management and governance challenges, including (1) heterogeneity among farmers with varying interests, leading to resistance to necessary changes, and (2) inefficient voting systems that hinder consensus on immediate decisions or cooperative strategic investments promptly (Candemir et al., 2021). These issues can thus prevent any attempt for reform, making the cooperatives themselves inefficient.

MATERIALS AND METHODS

Data and Outcome Variable

This study utilises data from the Cambodia Inter-Censual Agricultural Survey (CIAS) 2019, jointly conducted by the National Institute of Statistics (NIS) and the Ministry of Agriculture, Forestry and Fisheries (National Institute of Statistics, 2019). CIAS 2019 observes a sample of roughly 16,000 farm households across all 25 provinces throughout Cambodia, except for a few districts that are deemed highly urbanised.

The sampling method involved a two-step approach known as two-stage stratified sampling. Enumeration Areas (EAs) were designated as the primary units, and households involved in agricultural activities were the secondary units. A total of 1,350 EAs were to be selected, with 12 agricultural households chosen for each EA, resulting in a targeted sample size of 16,000 households. In cases where the chosen EA did not have 12 agricultural households, NIS distributed the remaining households to other EAs within the same province. This adjustment ensured that the overall sample size of the province remained consistent with the anticipated number of households for that province. It should be highlighted that the distribution of the 1,350 EAs among provinces was based on the proportion of rural households in each province. Notably, 50 EAs were automatically assigned to Phnom Penh, while the remaining 1,300 EAs were allocated to other provinces accordingly.

The survey took place between June and November 2019. It also provides comprehensive household information, including crop cultivation, livestock, aquaculture, and other agricultural activities. However, CIAS did not collect village-specific data, such as distance from the village to the nearest national road, seasonal labour movements, or soil types. Additionally, not all households provided complete information about themselves. Furthermore, some households have not been able to cultivate crops in the past 12 months. Therefore, due to incomplete information necessary for the study, these households had to be excluded from the data analysis. Our sample comprises 13,327 households, of which 1,358 (10.2%) participated in various farmer organisations and are considered treated households. The remaining 11,969 farm holdings did not participate in any association during the last 12-month period and served as the control or comparison group.

Table 1 highlights summary statistics of selected characteristics of the household sample disaggregated by their participation in farmer associations. It is worth noting that the average farm size of Cambodian households is 2.5 hectares. Treated households generally hold 2.8 hectares of cultivated land, while the non-treated or comparison groups possess slightly less at 2.6 hectares. However, statistically, there is no significant difference in farm size between households that participate in farmer cooperatives and those that do not. This result suggests that the amount of cultivated land among Cambodian farmers is rather small, consistent with findings from other studies. Government figures indicate that in 2017, 59% of Cambodian households owned agricultural land of less than 1 hectare, while 35% held between 1 and 3 hectares (NIS, 2017). The average household size is around four persons, which has fallen remarkably compared to the same indicator in 2013, in which the average household size was 4.6 (NIS, 2013). Moreover, most households are headed by males, with only about 20% of Cambodian families being female-headed, indicating a societal structure in some contexts.

Other characteristics of treated and non-treated households, including the age of the household head, their educational level, and the number of working adults

Table 1
Summary statistics of selected socioeconomic characteristics of treated and non-treated sample

Variables	**Mean (treated)** (1)	**Mean (non-treated)** (2)	***S.E*** (3)	***Diff* (t-test)** (1)-(2)
Land areas cultivated by households (ha)[a]	2.837	2.556	0.192	0.281
Household size	3.937	3.998	0.048	-0.06
Female-headed households (0/1)	0.224	0.223	0.012	0.002
Age of household head (years)[b]	48.682	48.540	0.330	0.142
Household head that completed high school (0/1)	0.098	0.097	0.009	0.001
Dependency ratio	0.506	0.530	0.018	-0.025
Number of working-age members (15–64)	2.765	2.775	0.039	-0.009
House with concrete wall (0/1)	0.129	0.152	0.010	-0.022**
Outstanding loans for agriculture production	0.305	0.243	0.013	0.061***
Outstanding loans from banks (0/1)	0.136	0.116	0.009	0.020**
Engagement in agro-processing activities (0/1)	0.045	0.034	0.005	0.011**
Experience with insects and crop diseases	0.148	0.116	0.009	0.033***
Engagement in aromatic rice farming (0/1)	0.195	0.139	0.010	0.056***
Engagement in mango plantation (0/1)	0.284	0.212	0.012	0.072***
Engagement in banana plantation (0/1)	0.222	0.189	0.012	0.033***
Engagement in cassava plantation (0/1)	0.096	0.107	0.009	-0.012
Engagement in cashew plantation (0/1)	0.115	0.094	0.009	0.021**
Share of agricultural income to total income (>40%)	0.619	0.526	0.015	0.092***
Obs.	1,358	11,969		

Notes: [a] observations for the treated group are 1,287 and 10,850 for the non-treated. One thousand one hundred ninety observations were excluded from the calculation because they did not report their land areas.
[b] observations for the control are 11,968.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Source: Authors' calculations using CIAS 2019

living in the household, are expected and of limited scientific interest. Moreover, the mean difference test does not suggest any remarkable variation between them. However, some notable distinctions are noteworthy: outstanding loans, engagement in agro-processing activities, experience in insects and crop diseases, engagement in cultivating commercial crops, and share of agricultural income to total income. The latter indicates that households participating in farmer associations tend to rely more on agriculture to generate income. Their engagement in planting multiple commercial crops is also higher compared to the control group. However, they are also likely to experience natural disasters relative to non-organised farmers. It suggests that the association might also be formed as a risk-sharing approach in terms of financial support or dissemination of knowledge. In other words, farmers who face frequent natural calamities consider the association as a method to cope with agricultural challenges. Descriptive statistics additionally show that only about 3.5% of households in Cambodia are engaged in agro-processing activities, a figure that needs to increase, implying that farm holdings are not fully integrated into the value chain. Despite these small numbers, cooperative farmers are significantly more likely to engage in agro-processing activities than non-members, which aligns with the abovementioned literature.

It should be noted that we further divided the treated households into two categories: those who officially participated in formal cooperatives registered at the provincial department of agriculture and those who joined informal associations unofficially acknowledged by local village headmen or commune chiefs (Theng et al., 2014) and regarding the number of households, 737 households, or 6% of the total sample, participated in a formal farmer association, whereas 873 households, or 7%, participated in an informal, unregistered farmer association such as farmer groups. Additionally, 252 households participated in formal and informal cooperatives and were counted in both groups. However, we do not present their summary statistics here; readers are referred to appendices A-1 and A-2 for such tables.

There are two indicators: sales and engagement in commercial crop plantation. The former is the total sales per hectare of all agricultural products during the previous 12 months, measured in KHR10,000 (Cambodian Riel). The latter is an index scale representing the diversification of commercialised crops, including aromatic rice, mango, banana, cashew nut, and cassava, which are considered cash crops and used by the agro-industry in Cambodia (World Bank, 2015). The index is computed using the following formula:

$$(Ch - Cmin)/(Cmax - Cmin)$$

where *Ch* represents the number of commercialised crops grown by the farm-holding; *Cmax* and *Cmin* are the maximum and minimum numbers of commercialised crops in the sample, respectively. The scale variable ranges from 0 to 1, with 1 indicating the highest level of crop diversification. Crop diversification is recognised as a strategy to minimise the negative effects of climate change on farmers in developing countries, improving efficiency and income stability (Mzyece & Ng'ombe, 2021), and increasing return to scale due to complementarity between rice and other crop production.

Table 2 presents the disparities in outcome variables between households participating in farmer cooperatives and those that did not. The differences are further analysed based on participation in formal or informal associations to gain a better understanding. The t-test results show no significant difference in sales of agricultural products between treated and non-treated households (Panel A). Regardless of the cooperative's status, this finding remains consistent across all panels. When comparing the total amount of household sales regardless of land area, there is no notable discrepancy among them. However, this does not hold for sales of agriculture products per hectare of planted area. In other words, member households can sell more of their cultivated products in proportion to the land they own. For instance, if member and non-member households each have a hectare of land, the former can significantly sell more of their cultivated products compared to the latter. Additionally, those who join associations are more likely to engage in commercial crop cultivation, with a probability of approximately 3.4%. Nevertheless, it is important to note that these descriptive statistics and t-test results should not be solely relied upon, as the differences observed may be due to chance and influenced by other factors. However, these findings serve as an initial indication for further detailed and empirical analysis. Similar results regarding outcome differences have also been discovered between households that are members of formal farmer organisations (Panel B) or informal farmer organisations (Panel C) and those that are not.

Table 2
Summary statistics of outcome variables by household participation in farmer associations

Variables	**Obs. (treated)**	**Obs. (non-treated)**	**Mean (treated) (1)**	**Mean (non-treated) (2)**	***S.E* (3)**	***Diff* (t-test) (1)-(2)**
Panel A	All sample					
Sales (in KHR10, 000) [a]	820	6,211	1,100.67	1,000.22	115.74	100.45
Sales per hectare of planted areas (in KHR10, 000) [b]	798	5,741	264.58	215.47	12.73	49.11***

Table 2 *(Continue)*

Variables	**Obs. (treated)**	**Obs. (non-treated)**	**Mean (treated) (1)**	**Mean (non-treated) (2)**	***S.E* (3)**	***Diff* (t-test) (1)-(2)**
Engagement in commercial crop plantation (0–1 index)	1,358	11,969	0.18	0.15	0.005	0.03***
Panel B			Formal			
Sales (in KHR10, 000)	462	6,211	1,211.27	1,000.22	151	211.05
Sales per hectare of planted areas (in KHR10, 000)	449	5,741	290.87	215.47	16.74	75.41***
Engagement in commercial crop plantation (0–1 index)	737	11,969	0.18	0.15	0.007	0.03***
Panel C			Informal			
Sales (in KHR10, 000)	498	6,211	1,074.78	1,000.22	144.16	74.56
Sales per hectare of planted areas (in KHR10, 000)	484	5,741	294.47	215.47	16.08	79.01***
Engagement in commercial crop plantation (0–1 index)	873	11,969	0.17	0.15	0.01	0.03***

Notes: [a]6,296 households (47.2% of the total observations) were excluded from the analysis because they did not report sales value in the past 12 months prior to the survey date.
[b]6,788 households (50.9% of the total observations) were excluded for similar reason
s.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Source: Authors' calculations using CIAS 2019

Estimation Strategy

As this study utilises cross-sectional data, addressing potential selection bias is crucial. One approach to achieve this is using either the Instrumental Variable (IV) or the Propensity Score Matching (PSM) method. In principle, the IV approach is preferred over PSM. However, finding a valid IV correlated with association membership but has no direct effect on outcome variables such as sales is arguably very difficult, if not impossible, making it empirically impractical. Therefore, this study employs PSM to investigate the causal effect of participation in farmer associations.

The PSM method has also been used elsewhere to evaluate the impacts of program interventions when limited to using cross-sectional data, as in our case, because it can minimise selection bias by reducing the differences in observable characteristics of households that are members of farmer associations and those that are not (Abebaw et al., 2010; Rosenbaum & Rubin, 1985).

Moreover, this method is highly effective and increasingly popular when the dataset comprises a sufficiently large sample size, such as the one we use. In general, a large sample size presents a considerable advantage for matching purposes, as it increases statistical power and reduces bias in impact estimation (Khandker et al., 2010). PSM involves a two-step procedure, beginning with estimating the probability that a farm household will participate in the cooperative, commonly known as the propensity score. The estimation is typically conducted using logit regression and can be best understood through the following econometric specification:

$$P(X_i) = G(\alpha + X_i'\beta) \quad (1)$$

Where subscript i indexes individual households, T is the binary treatment variable, which takes the value of 1 if a farm household participates in a formal or informal association, and 0 otherwise. The control group comprises households that do not participate in any agricultural organisation. G is a function strictly taking on values between 0 and 1 and following the logistic distribution; $G(z) = \frac{e^z}{1+e^z}$; α is the intercept; $X'\beta$ equal to $\beta_1 X_1 + \beta_2 X_2 + \cdots + B_k X_k$ where X is a vector of household attributes that help explain the probability of participating in a formal or informal farmer association. These include *household size* which is defined as the total number of people in a household (representing the available farm labour supply); *female,* a dummy variable recorded as 1 if the household head is female and 0 otherwise; *age,* the age of household head in years; *education,* a binary variable taking the value of 1 if household head completed high school and 0 otherwise; *dependency,* defined as the ratio of dependents aged 0 to 14 and over 65 to adult household members aged between 15 and 64; *concrete house wall,* an indicator variable taking the value of 1 if a household's wall is made of concrete and 0 otherwise (used as a proxy for household wealth in the absence of other useful asset variables); and finally, *insects and crop problems,* a dummy variable indicating farm households that experienced insects and crop diseases in the previous 12 months.

The selection of these control variables is based on the general research literature and Cambodia-specific studies on the impact of farmer association on various household indicators (Abebaw & Haile, 2013; Ofori et al., 2019; Theng et al., 2014). After the model is estimated in the first step, the propensity score is predicted for every treatment and control group sample. In the second step, we will match observations in the treatment group with those in the control group based on the comparability of their propensity score using several matching algorithms—Nearest Neighbour (NN), Kernel, and Stratification.

We also address the region of common support to avoid comparing incomparable samples, which could result in a certain degree of evaluation bias. The samples with comparable propensity scores are dropped from the data analysis. Additionally, we compare the covariates X_i before and after matching to validate the quality of our matching. It can be achieved by examining the mean absolute bias, which is expected to decrease significantly after matching. Furthermore, the standardised bias of each independent variable in the logistic regression before and after matching is also used to assess whether there are systematic differences in the means of the covariates across both groups (Rosenbaum & Rubin, 1985). In other words, no significant differences in the covariates between both groups should be found after such matching, suggesting that the observed characteristics of samples between the treatment and the control groups are comparable. To this end, Caliendo and Kopenig (2008) propose a rule of thumb that a standardised bias below 3% or 5% after the matching should be seen as sufficient. In addition, we follow Sianesi's (2004) suggestion to compare the Pseudo-R^2 before and after matching, expecting the Pseudo-R^2 before matching to be higher than that after matching. In addition, the P-values of likelihood ratio tests for joint significance in the logit model should be rejected after matching, indicating no systematic differences in the distribution of observable independent variables between both groups.

Furthermore, the PSM method requires two necessary assumptions: conditional independence and common support or overlapping conditions. The former is sometimes known as the exogeneity assumption, which simply states that participation in the farmer association is based entirely on observed household characteristics. We can attempt to hold the conditional independence assumption valid by controlling for many observable household characteristics that can affect farmer association participation, as Khandker et al. (2010) recommended. It leads us to our second assumption: the overlap condition in PSM, which requires that observations in the treatment group have comparable counterparts in the control group within the propensity score distribution. It is why data drawn from a representative sample is preferred, as this assumption is likely to hold if the sample size is quite large, ensuring a sizeable overlap in the propensity distribution and, in turn, increasing the precision of the estimation.

RESULTS AND DISCUSSION

We now proceed to address the initial questions posed. First, we will estimate the propensity of participation in a farmer cooperative and examine the observable factors that may explain such participation. To achieve this, we will utilise a Stata command called '*pscore*' to estimate Equation (1) above and to test the balancing property.

Table 3 presents the results from the logistic regression of participation in farmer associations, including the marginal effects. A balancing test across all specifications confirms that balancing properties are satisfied. However, the overall goodness of fit (*pseudo* R^2) is not strong, ranging from 0.001 to 0.008, although all specifications are statistically significant. Interestingly, some household-level characteristics do

Table 3
Probability of participating in farmer cooperative (Marginal effect)

	All samples	**Formal**	**Informal**
	(1)	(2)	(3)
Household size	-0.018	-0.008	-0.036
	(0.019)	(0.025)	(0.023)
Female-headed households (0/1)	-0.006	-0.141	0.077
	(0.071)	(0.098)	(0.085)
Age of household head of holding	0.006	0.009	0.013
	(0.028)	(0.038)	(0.034)
Age squared of the household head holding	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)
Household head completed high school (0/1)	0.049	0.141	0.063
	(0.098)	(0.125)	(0.119)
Dependency ratio	-0.044	-0.004	-0.062
	(0.051)	(0.067)	(0.064)
Concrete house wall (0/1)	-0.187**	-0.068	-0.072
	(0.086)	(0.110)	(0.101)
Experience with insects and crop diseases (last 12 months)	0.277*	0.671*	0.102
	(0.082)	(0.096)	(0.106)
All controls	11,969	11,969	11,969
Treatment	1,358	737	873
Observations	13,326	12,705	12,841
Prob > x^2	0.0136	0.0000	0.4139
Pseudo R^2	0.002	0.008	0.001
Log-likelihood	-4377.976	-2789.642	-3185.554
Balancing test	Satisfied	Satisfied	Satisfied
# Of blocks	2	4	1

Notes: The dependent variable takes the value of 1 if the sample households are members of agricultural cooperatives and 0 otherwise. Standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Source: Authors' calculations using CIAS 2019

not appear to influence the decision to join the cooperatives, a finding consistent with Ofori et al. (2019) in Cambodia and Fischer and Qaim (2012) in Kenya, who observed similar results. The similarity in socioeconomic characteristics between Kenyan households, cooperative members and non-members, as evidenced by Kernel density distribution of propensity scores of treated and untreated groups before and after matching, is provided in Appendix B. This close similarity in propensity scores is crucial as it enables a robust comparison of outcome variables.

We will now discuss the factors potentially influencing the decision to join a cooperative or association. These factors include having experienced problems with insects and crop diseases in the previous 12 months and having a concrete house wall (more or less a proxy for household assets). Those who are poorer and have faced natural disasters are 27.7% more likely to participate in farmer organisations than those who have not faced such challenges. It suggests that, for poor Cambodian farmers, joining a cooperative tends to be a risk-sharing strategy. They might also see it as a knowledge-sharing opportunity that provides technical know-how to cope with environmental calamities. Regardless, the first stage estimation results enable us to construct the propensity score on which control groups are established, and the outcomes of the two groups are compared.

Table 4 presents the main estimation results of the effect of participation in farmer cooperatives on agriculture sales per hectare of planted area and engagement in commercial crop plantation. The matching estimators are propensity score (Column 4) and nearest neighbour (Column 5), and we use both. Propensity score matching does not allow for bias adjustment, so we complement that by using the nearest neighbour matching approach and comparing the outputs. Additionally, we perform several postestimation after-matching analyses to check the robustness of the estimates by the main matching approaches. The results of such estimates are presented in Columns 7, 8, and 9. Given the inclusive results of the effect of specification on outcome variables, we use propensity score from the same first-step selection equation for all outcome variables examined (Marchetta & Sim, 2021).

Overall, the matching outcomes show a positive and significant impact of farmer association participation on crop sales per hectare of planted area and crop diversification. The effects range from 11.7% to 15.7% for PS matching (Panel A, Column 4) or 13.7% to 15.4% for Nearest Neighbour matching adjusted for potential explanatory variable bias (Panel A, Column 5). Furthermore, the results are robust, whether based on the number of nearest neighbour matches or other estimators on the matched sample. To put it another way, the results on agriculture sales per hectare of planted area are similar even when we separate the sample between those who participate in formal and informal organisations, as shown in Appendix C-1 and C-2, respectively. Other matching methods, including Kernel and Stratification, also give similar results, so we omit them due to space limitations. In addition, we also carried out OLS and fixed-effects regressions to compare the results. However, we did not rely on these models because the coefficients are distorted by selection bias, as discussed earlier, despite controlling for other independent variables in the regression. Nevertheless, complete results are available upon request.

In sum, our positive findings are consistent with those of Ofori et al. (2019), who found that participation in Cambodia's agricultural cooperatives substantially impacts farm revenue. Member households

Table 4
The effect of participation in farmer community or organisation on agriculture sales per hectare of planted area and engagement in commercial crop plantation

n	***Obs.*** Treated	Matched Controls	ATET	ATET Adj.	OLS (Unmatched sample)	**Matched sample** *Diff* t-test	OLS	FE
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A				**Outcome: Sales per hectare planted area (log)**				
1	820	252	0.141*** (0.005)	0.129*** (0.049)		0.119 (0.095)	0.130* (0.072)	0.030 (0.138)
2	820	512	0.146*** (0.050)	0.131*** (0.049)		0.034 (0.077)	0.054 (0.060)	0.149 (0.111)
3	820	757	0.136*** (0.049)	0.126*** (0.049)		0.087 (0.070)	0.071 (0.055)	0.175* (0.100)
4	820	987	0.130*** (0.049)	0.126*** (0.049)		0.134** (0.066)	0.116** (0.052)	0.253** (0.090)
5	820	1,212	0.136*** (0.049)	0.125*** (0.049)	0.121** (0.06)	0.140** (0.063)	0.118** (0.050)	0.227*** (0.084)
6	820	1,430	0.129*** (0.049)	0.124*** (0.049)		0.144** (0.060)	0.108** (0.049)	0.202** (0.081)
7	820	1,636	0.132*** (0.049)	0.121*** (0.049)		0.138** (0.060)	0.072 (0.05)	0.168** (0.080)
8	820	1,828	0.134*** (0.063)	0.122*** (0.063)		0.144 (0.059)	0.074** (0.049)	0.174** (0.078)
9	820	2,001	0.130*** (0.049)	0.128*** (0.049)		0.158*** (0.058)	0.079 (0.049)	0.176** (0.076)
10	820	2,161	0.128*** (0.049)	0.128*** (0.049)		0.176** (0.057)	0.099*** (0.048)	0.201*** (0.075)
Panel B				**Outcome: Crop Diversification (0-1 index)**				
1	1,358	329	0.033*** (0.006)	0.032*** (0.006)		0.043*** (0.012)	0.044*** (0.012)	0.047*** (0.013)
2	1,358	654	0.034*** (0.006)	0.033*** (0.006)		0.039*** (0.009)	0.042*** (0.009)	0.043*** (0.013)
3	1,358	971	0.034*** (0.006)	0.033*** (0.006)		0.040*** (0.007)	0.042*** (0.009)	0.043*** (0.013)
4	1,358	1,275	0.033*** (0.006)	0.033*** (0.006)		0.040*** (0.007)	0.044*** (0.007)	0.040*** (0.013)
5	1,358	1,567	0.033*** (0.006)	0.033*** (0.006)	0.033*** (0.005)	0.041*** (0.007)	0.045*** (0.007)	0.052*** (0.009)
6	1,358	1,840	0.033*** (0.006)	0.033*** (0.006)		0.041*** (0.006)	0.044*** (0.007)	0.041*** (0.013)
7	1,358	2,106	0.033*** (0.006)	0.033*** (0.006)		0.040*** (0.006)	0.044*** (0.006)	0.034*** (0.013)
8	1,358	2,362	0.033*** (0.006)	0.033*** (0.006)		0.041*** (0.006)	0.045*** (0.006)	0.050*** (0.013)
9	1,358	2,609	0.033*** (0.006)	0.033*** (0.006)		0.040*** (0.005)	0.044*** (0.006)	0.027*** (0.013)
10	1,358	2,853	0.033*** (0.006)	0.033*** (0.006)		0.040*** (0.005)	0.043*** (0.006)	0.036*** (0.013)

Notes: ATET is the average treatment effect on the treated, whereas ATET Adj. is the ATET adjusted for biases of the covariates. Given that the sales value is in logarithmic form, resulting in a semilogarithmic estimation, we employ the approach by Halvorsen and Palmquist (1980) for coefficient interpretation. That is, $\%\Delta\beta = (e^{\beta} - 1) \times 100$. Standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Source: Authors' calculations using CIAS 2019

can sell more of their cultivated products than non-members. The same discovery is also documented in Rwanda's coffee sector, where cooperative membership positively influences farmer's productivity (Ortega et al., 2019). A possible explanation for such findings would include disseminating information on agricultural technology, which increases productivity (Zhang et al., 2020), and improving market information and bargaining power (Wossen et al., 2017). In addition, a cooperative's name might act like a collective business brand signalling the quality of products to consumers, who, in turn, can develop a positive view of certain producers or groups of producers (Grashuis & Magnier, 2018). Furthermore, as producer theory predicts, product differentiation leads to higher sales and incomes.

We also discover a significant influence of farmer associations on the household crop diversification index (Panel B). That is, farming households who participate in such associations are observed to be 3.3% more likely to adopt commercial crops. The effect is statistically significant even at 1%. Similar gains are also observed for farming households participating in formal or informal farmer organisations (Appendix C-1 and C-2, Panel B). Again, the results can be attributable to the members' improvement in technical efficiency, as found by Mzyece and Ng'ombe (2021) and Wollni and Brümmer (2012). In particular, Theng et al. (2014) assert that the significant effects of Cambodian farmer associations largely stem from better technological understanding and usage. We can thus understand that besides providing a risk-sharing mechanism, the country's cooperatives also function as a knowledge-sharing platform for farmers. It explains why those who had experienced natural disasters in the previous 12 months were likelier to join an association to learn methods to minimise the damage of such catastrophes.

From a social sciences point of view, the participation of Cambodian farmers in agricultural cooperatives highlights the potential for these organisations to promote social cohesion and community-building (Lang & Novy, 2014). Farmers have developed stronger social networks and a sense of collective identity by working together, fostering mutual trust and cooperation. Thus, it facilitated the sharing of knowledge, the adoption of new farming practices, and the collective bargaining power of the farmers, leading to better market access and higher incomes. Furthermore, the humanities perspective offers insights into the cultural and societal implications of agricultural cooperatives in Cambodia. Research studies in anthropology and sociology have explored how these organisations intersect with local traditions, values, and power dynamics (Schneiberg et al., 2008). For instance, the role of cooperatives in preserving and transmitting traditional agricultural knowledge and practices can contribute to the preservation of cultural heritage (Moscatelli et al., 2017). Additionally, the cooperative model can provide a platform for marginalised groups, such as women and ethnic minorities, to participate more actively in the agricultural sector and assert their rights and interests (Mhembwe & Dube, 2017). Integrating these social sciences and humanities perspectives illustrates how the cooperative model in Cambodia's agriculture sector goes beyond just economic impacts. It fosters more equitable, culturally grounded, and psychosocially empowered rural communities—a vital foundation for preserving Cambodia's rich civilisation and advancing human development sustainably.

CONCLUSION

Using the PSM approach, this study investigates the impact of farmer associations on agricultural sales per hectare of planted area and crop diversification, two indicators largely overlooked in the literature. Unlike most previous studies, which rely on small sample sizes and/or focus on a specific crop, we employ the Cambodia Inter-Censal Agricultural Survey 2019 and used multiple commercial crops to measure rural households' agricultural success. To the best of our knowledge, ours is the first research study conducted in Cambodia and one among several in the region that can utilise such data and outcome variables. As a result, our study contributes not only new and strong empirical evidence on the influence of farmer cooperatives on various household performance indicators but also offers significant potential in offering Cambodian policymakers to gain applicable knowledge and evidence-based policy implications to enhance agricultural insights for farmers and their communities.

Findings show that many rural households see cooperatives as a risk-sharing strategy and that member households benefit from participating in such organisations in terms of increasing sales as well as knowledge on crop diversification. A possible explanation for this is that through formal or informal training, farmers can learn about the advantages of crop diversification and receive support in terms of inputs such as seeds and technology. However, we cannot clearly understand how cooperatives influence crop diversification. In contrast, the effect on sales is more likely to result from increased market and bargaining power, as well as access to information about potential markets.

Implications for Theory and Practice

Given the central role of agriculture in rural income, expanding and strengthening farmer cooperative management is critical for achieving sustainable development. However, at their current development stage, the Cambodian agricultural cooperatives still largely depend financially on donors, which means their operations will not be sustainable, and the cooperatives themselves will go bankrupt once the funding is exhausted. Therefore, establishing a sustainable financing model is crucial for their survival. Additionally, these associations' governance and financial management should be autonomous and streamlined to minimise bureaucratic obstacles. The government can also play a big role in helping establish, improve, and support cooperatives by providing technical assistance, including how to set up a local cooperative and other crucial training on management, farming technologies, and know-how. Research evidence encouraged the role of government intervention in promoting collective action, particularly for the farmer association (Li et al., 2023).

Limitation of the Study

It should be highlighted again that PSM requires two assumptions, and with these assumptions come inherent limitations that must be acknowledged. Despite being a method for causal impact evaluation (Imbens & Wooldridge, 2009), PSM has a few definite drawbacks. One major limitation is that the approach assumes selection bias stems mainly from observed characteristics, thereby not addressing unobservable factors that could influence the probability of receiving treatment (Cerulli, 2015; Cunningham, 2021; Khandker et al., 2010). One potential solution is to include household or community covariates that are likely fixed before and after treatment or to construct pre-treatment variables that are unlikely to be affected by treatment. With the current dataset, particularly with regard to the limitation on covariates surveyed, we can only adopt the former solution. Therefore, in general terms, the Propensity Score Matching method significantly reduces selection bias but does not eliminate it. Nevertheless, bias in PSM estimates in our case can be low and thus negligible because our study and data meet all three broad requirements postulated by Heckman et al. (1997, 1998). First, data on treatment and control groups were collected using the same survey instrument, by the same interviewers, and during the same survey period. Second, our data are derived from a nationally representative survey with a large sample size, as described earlier. Third, the large sample size in the comparison group facilitates a smoother matching process.

Recommendations for Future Research

Future research on farmer associations could explore two key areas. First, measuring the impact of these associations through rigorous impact evaluation research can help establish causal relationships. However, such quantitative studies may not fully explain the underlying mechanisms driving the observed impacts. In this regard, qualitative research would provide a more comprehensive understanding. Second, while existing studies have found positive effects of farmer association membership, the net economic benefits to farming households remain unclear because the analysis has not factored in the costs incurred by members, such as membership fees or in-kind contributions to cooperative operations. Essentially, the monetary gains from membership may be smaller than the direct and opportunity costs borne by the households. Conducting a thorough cost-benefit analysis could be a fruitful area for future research to ascertain the true economic implications of farmer association membership.

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APPENDICES

Appendix A.1: Summary statistics of selected socioeconomic characteristics (formal)

Variables	**Mean (treated) (1)**	**Mean (non-treated) (2)**	***S.E* (3)**	***Diff* (t-test) (1)-(2)**
Land areas cultivated by households (ha)[a]	3.132	2.556	0.256	0.576**
Household size	3.986	3.998	0.063	-0.011
Female-headed households (0/1)	0.200	0.223	0.016	-0.023
Age of household head (years)[b]	48.711	48.540	0.438	0.171
Household head completed high school (0/1)	0.109	0.097	0.012	0.012
Dependency ratio	0.519	0.530	0.025	-0.012
Number of working-age members (15-64)	2.799	2.775	0.052	0.025
House with concrete wall (0/1)	0.143	0.152	0.014	-0.009
Outstanding loans for agriculture production	0.350	0.243	0.017	0.107***
Outstanding loans from banks (0/1)	0.154	0.116	0.012	0.037***
Engagement in agro-processing activities (0/1)	0.059	0.034	0.007	0.025***
Experience of insects and crop diseases	0.204	0.116	0.013	0.088***
Engagement in aromatic rice farming (0/1)	0.177	0.139	0.013	0.039***
Engagement in mango plantation (0/1)	0.285	0.212	0.016	0.072***
Engagement in banana plantation (0/1)	0.227	0.189	0.015	0.038**
Engagement in cassava plantation (0/1)	0.102	0.107	0.012	-0.005
Engagement in cashew plantation (0/1)	0.102	0.094	0.011	0.008
Share of agricultural income to total income (>40%) (0/1)	0.599	0.526	0.019	0.072***
Obs.	737	11,969		

Source: Authors' calculations using Cambodia Inter-Censual Agricultural Survey 2019.

Notes: [a] observations for the treated group are 695 and 10,850 for the non-treated. 1,161 observations were excluded from the calculation because they did not report their land areas.

[b] observations for the control are 11,968.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix A.2: Summary statistics of selected socioeconomic characteristics (informal)

Variables	**Mean (treated) (1)**	**Mean (non-treated) (2)**	***S.E* (3)**	***Diff* (t-test) (1)-(2)**
Land areas cultivated by households (ha)[a]	2.579	2.556	0.232	0.023
Household size	3.877	3.998	0.058	-0.120**
Female-headed households (0/1)	0.239	0.223	0.015	0.016
Age of household head (years)[b]	48.488	48.540	0.405	-0.052
Household head completed high school (0/1)	0.101	0.097	0.011	0.004
Dependency ratio	0.494	0.530	0.022	-0.036
Number of working-age members (15-64)	2.722	2.775	0.048	-0.053
House with concrete wall (0/1)	0.143	0.152	0.013	-0.008
Outstanding loans for agriculture production	0.287	0.243	0.015	0.043***
Outstanding loans from banks (0/1)	0.123	0.116	0.011	0.007*
Engagement in agro-processing activities (0/1)	0.046	0.034	0.007	0.012
Experience of insects and crop diseases	0.127	0.116	0.011	0.012
Engagement in aromatic rice farming (0/1)	0.184	0.139	0.012	0.044***
Engagement in mango plantation (0/1)	0.272	0.212	0.015	0.059***
Engagement in banana plantation (0/1)	0.197	0.189	0.014	0.009
Engagement in cassava plantation (0/1)	0.100	0.107	0.011	-0.007
Engagement in cashew plantation (0/1)	0.118	0.094	0.011	0.024**
Share of agricultural income to total income (>40%) (0/1)	0.637	0.526	0.018	0.111***
Obs.	873	11,969		

Source: Authors' calculations using Cambodia Inter-Censual Agricultural Survey 2019.

Notes: [a] observations for the treated group are 829 and 10,850 for the non-treated. 11,163 observations were excluded from the calculation because they did not report their land areas.

[b] observations for the control are 11,968.

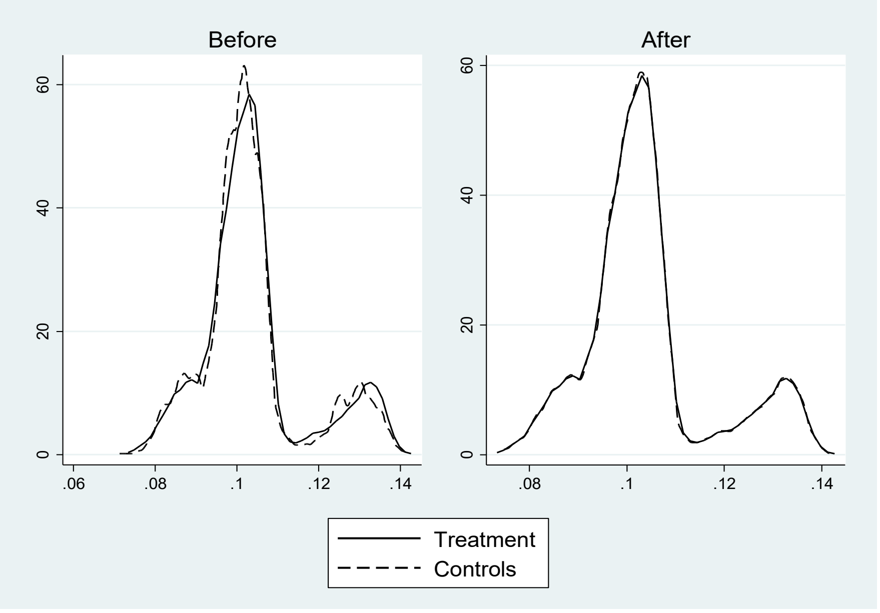
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Appendix A.3: One-way analysis of variance

		Sum of square	df	Mean square	F	Sig.
(1)	Between group	2.0252e+7	2	1.0126e+7		
	Within group	6.8192e+10	7,028	9.7028e+6	1.04	0.352
	Total	6.8212e+10	7,030	9.7029e+6		
(2)	Between group	2.3996e+6	2	1,199,821.53		
	Within group	7.4192e+10	6,536	11,3513.887	10.570	0.001
	Total	7.4432e+10	6,538	113846.193		
(3)	Between group	1.4279	2	0.713		
	Within group	396.492	13,324	0.029	23.990	0.001
	Total	397.920	13,326	0.029		

Source: Authors' calculations using Cambodia Inter-Censual Agricultural Survey 2019.
Notes: (1) sales; (2) sales per hectare; (3) engagement in commercial crop plantation. The grouping is 1 for non-treated, 2 for participation in formal or in informal association.

Appendix B: Kernel density distribution of propensity score of the treated and non-treated groups before and after matching (all sample)



Appendix C.1: The effect of participation in farmer cooperatives on sales and engagement in commercial crop plantation (formal)

n	***Obs.*** Treated	Matched Controls	ATET	ATET Adj.	OLS (Unmatched sample)	**Matched sample** ***Diff*** t-test	OLS	FE
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Outcome: Sales per hectare of land (log)								
1	462	201	0.138** (0.067)	0.117* (0.067)	0.112* (0.060)	-0.112 (0.117)	0.177* (0.097)	-0.050 (0.151)
2	462	399	0.147** (0.067)	0.127* (0.067)		0.035 (0.095)	0.062 (0.081)	0.147 (0.120)
3	462	591	0.142** (0.066)	0.111* (0.066)		0.104 (0.087)	0.098 (0.075)	0.186* (0.106)
4	462	776	0.138** (0.066)	0.104 (0.066)		0.136* (0.082)	0.124* (0.070)	0.200** (0.096)
5	462	953	0.131** (0.066)	0.104 (0.066)		0.131* (0.079)	0.102 (0.067)	0.177* (0.091)
6	462	1,126	0.123* (0.065)	0.106 (0.066)		0.136* (0.076)	0.088 (0.066)	0.163* (0.087)
7	462	1,294	0.122* (0.066)	0.105 (0.066)		0.134* (0.075)	0.044 (0.067)	0.160* (0.087)
8	462	1,454	0.122* (0.066)	0.106 (0.066)		0.142* (0.074)	0.041 (0.066)	0.179** (0.084)
9	462	1,610	0.122* (0.066)	0.110* (0.066)		0.159** (0.073)	0.044 (0.065)	0.196** (0.082)
10	462	1,753	0.123* (0.066)	0.108 (0.066)		0.175** (0.072)	0.067 (0.065)	0.203** (0.081)
Panel B: Outcome: Crop Diversification (0-1 index)								
1	737	266	0.026*** (0.007)	0.025*** (0.007)	0.027*** (0.006)	0.030** (0.013)	0.031** (0.013)	0.038*** (0.014)
2	737	526	0.027*** (0.007)	0.025*** (0.007)		0.028*** (0.009)	0.031*** (0.010)	0.033*** (0.014)
3	737	784	0.027*** (0.007)	0.026*** (0.007)		0.035*** (0.009)	0.037*** (0.009)	0.054*** (0.014)
4	737	1,032	0.027*** (0.007)	0.026*** (0.007)		0.034*** (0.014)	0.037*** (0.008)	0.034** (0.014)
5	737	1,275	0.028*** (0.007)	0.026*** (0.007)		0.036*** (0.007)	0.038*** (0.008)	0.045*** (0.014)
6	737	1,512	0.028*** (0.007)	0.027*** (0.007)		0.036*** (0.007)	0.037*** (0.008)	0.042*** (0.014)
7	737	1,738	0.028*** (0.007)	0.027*** (0.007)		0.037*** (0.007)	0.039*** (0.007)	0.047*** (0.014)
8	737	1,961	0.028*** (0.007)	0.027*** (0.007)		0.037*** (0.007)	0.040*** (0.007)	0.049*** (0.014)
9	737	2,171	0.028*** (0.007)	0.027*** (0.007)		0.037*** (0.007)	0.039*** (0.007)	0.028*** (0.014)
10	737	2,376	0.028*** (0.007)	0.026*** (0.007)		0.036*** (0.007)	0.039*** (0.007)	0.039*** (0.014)

Source: Authors' calculations using Cambodia Inter-Censual Agricultural Survey 2019.

Notes: ATET is the average treatment effect on the treated, whereas ATET Adj. is the ATET adjusted for biases of the covariates. We also controlled for other variables for the ordinary least square and fixed effect regressions. Given limited space, coefficients are not presented but available upon request. Standard errors are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Appendix C.2: The effect of participation in farmer cooperatives on sales and engagement in commercial crop plantation (informal)

	Obs.					Matched sample		
n	**Treated**	**Matched Controls**	**ATET**	**ATET Adj.**	**OLS (Unmatched sample)**	***Diff* t-test**	**OLS**	**FE**
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Outcome: Sales per hectare of land (log)								
1	484	192	0.201*** (0.063)	0.185*** (0.063)		0.072 (0.117)	0.140 (0.092)	0.047 (0.136)
2	484	383	0.181*** (0.063)	0.180*** (0.063)		0.066 (0.094)	0.071 (0.077)	0.159 (0.117)
3	484	572	0.180*** (0.064)	0.177*** (0.063)		0.122 (0.085)	0.081 (0.070)	0.219** (0.106)
4	484	758	0.174*** (0.063)	0.181*** (0.063)		0.175** (0.079)	0.135** (0.066)	0.303*** (0.097)
5	484	938	0.178*** (0.063)	0.180*** (0.063)	0.182*** (0.058)	0.193** (0.076)	0.151** (0.064)	0.279*** (0.091)
6	484	1,109	0.176*** (0.063)	0.180*** (0.063)		0.208** (0.074)	0.146** (0.063)	0.286*** (0.088)
7	484	1,277	0.171*** (0.063)	0.173*** (0.063)		0.200*** (0.073)	0.112* (0.063)	0.246*** (00.087)
8	484	1,435	0.172*** (0.063)	0.172*** (0.063)		0.195*** (0.072)	0.113* (0.062)	0.229*** (0.084)
9	484	1,584	0.173*** (0.063)	0.182*** (0.063)		0.206*** (0.071)	0.120** (0.061)	0.237*** (0.082)
10	484	1,730	0.169*** (0.063)	0.184*** (0.063)		0.220** (0.07)	0.138** (0.061)	0.268*** (0.081)
Panel B: Outcome: Crop Diversification (0-1 index)								
1	873	268	0.026*** (0.007)	0.026*** (0.007)		0.037*** (0.013)	0.040*** (0.013)	0.033*** (0.014)
2	873	534	0.028*** (0.007)	0.026*** (0.007)		0.037*** (0.010)	0.040*** (0.010)	0.033*** (0.014)
3	873	797	0.027*** (0.007)	0.026*** (0.007)		0.035*** (0.009)	0.039*** (0.009)	0.032*** (0.014)
4	873	1,054	0.028*** (0.007)	0.026*** (0.007)		0.034*** (0.008)	0.038*** (0.008)	0.023*** (0.014)
5	873	1,308	0.027*** (0.007)	0.026*** (0.007)	0.026*** (0.006)	0.035*** (0.007)	0.039*** (0.008)	0.030*** (0.014)
6	873	1,557	0.027*** (0.007)	0.026*** (0.007)		0.036*** (0.007)	0.038*** (0.007)	0.030*** (0.015)
7	873	1,802	0.027*** (0.007)	0.026*** (0.007)		0.035*** (0.007)	0.039*** (0.007)	0.033*** (0.015)
8	873	2,045	0.027*** (0.007)	0.026*** (0.007)		0.036*** (0.007)	0.040*** (0.007)	0.046*** (0.015)
9	873	2,286	0.027*** (0.007)	0.026*** (0.007)		0.035*** (0.007)	0.038*** (0.007)	0.024*** (0.014)
10	873	2,523	0.027*** (0.007)	0.027*** (0.007)		0.034*** (0.007)	0.037*** (0.007)	0.025*** (0.015)

Source: Authors' calculations using Cambodia Inter-Censual Agricultural Survey 2019.
Notes: ATET is the average treatment effect on the treated, whereas ATET Adj. is the ATET adjusted for biases of the covariates. We also controlled for other variables for the ordinary least square and fixed effect regressions. Given limited space, coefficients are not presented but available upon request. Standard errors are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.