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Vatana Chea

Cambodia University of Technology and Science (CamTech)

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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 very large sample size of 16,000 small-scale producers. Additionally, we perform a robustness check to make sure that 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, moreover, show a significantly positive impact of participating in the cooperatives on sales and on the crop diversification index. This study thus advocates increasing technical support and implementing policies by the government to help cooperatives thrive and expand.

JEL Classification: Q22, J54.

Keywords: impact, agriculture, farmer association, Cambodia

Corresponding author:

Vatana CHEA*

Center for Socio-Economic Research

Cambodia University of Technology and Science (CamTech)

Phnom Penh, Kingdom of Cambodia

Email: vatana.chea@camtech.edu.kh

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Impact of Farmer Associations on Sales and Crop Diversification

CHEA Vatana, KEO Socheat, Yoeun Sereyvath

November, 2021

1 Introduction

The growth of farmer organizations including associations, cooperatives, communities, and groups, has been remarkable in many parts of the world, especially in the context of imperfect markets (Candemir et al., 2021), in which such organizations¹ are seen as an effective institutional response to address the challenges of market failure. In 2015, Europe had over 51,000 farmer associations, with a turnover of approximately USD 415 billion (Grashuis & Su, 2019). It is also worth noting that each rural village in Africa claims to have at least one local farmer association (Wang et al., 2019)-not to mention another 1,871 or so organizations with a total of more than two million members in the United States during the same period. To put this into perspective, in some economies in the European Union such as France, Austria, and the Nordic countries, the share of agricultural products marketed through associations comprises more than 50 percent (Bijman & Liopoulos, 2014). Due to their considerable importance, farmer associations have drawn a lot of attention among scholars and the governments of developing countries, especially in the era of intensification of globalization and market liberalization (Abeba & Haile, 2013).

But despite the fact that farmer associations are common in both the developed and developing world, their impact is not clearly understood even though more and more research on them has been initiated, especially since the last decade (Bizikova et al., 2020, and references therein). Theoretically speaking, it is believed that farmer organizations improve profit, income, and productivity of agricultural smallholders in rural areas by increasing their collective bargaining power. In addition, such organizations are claimed to improve product quality and access to farming knowledge and technologies, minimize logistic and marketing cost due to economies of scale, reduce information asymmetry, and connect farmers to bigger and international markets (Ito et al., 2012). Therefore, cooperation with such organizations is deemed an effective route out of poverty for small-scale producers and plays a crucial role in the improvement of farm sustainability.

In fact, many studies have proven such a claim. For instance, Bernard et al. (2008), Wollni and Zeller (2007), and Wang et al. (2019) show that joining a farmer association leads to a significant increase in prices received and agricultural profit. Likewise, a study

¹In this study, farmer associations, farmer cooperatives, and farmer organizations are used interchangeably.

in Nigeria notes a higher technical efficiency among members of agricultural cooperatives as compared to those who do not join any organization at all (Olagunju et al., 2021). In Kenya, members of agricultural cooperatives sell bananas for 23 percent higher than do non-members (Fischer & Qaim, 2012). Other empirical studies document a strong and positive influence of participation in farmer associations on other indicators of member performance such as fertilizer and pesticide adoption (Abebaw & Haile, 2013), thus raising yields and household income (Ma & Abdulai, 2016) and reducing cropland abandonment (Ma & Zhu, 2020). Furthermore, agricultural cooperatives improve the use of technology, 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 condition or, at worst, have an adverse effect, depending on the indicators that we use to measure the impacts. In particular, Malvido Perez Carletti et al. (2018) did not find any benefits of joining a farmer organization at all. In fact, using multilevel analysis, they observed a negative impact of farmer cooperatives on the price of wine in Argentina. Similarly, empirical study of the Austrian wine market indicates that members of the cooperatives had high tendency to free-ride on quality, and as a result wines produced by the cooperatives were generally of 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. Reviewing the empirical literature, Barrett (2008) also claims that while farmer associations have significant positive impacts on high-value crops, there is little evidence to prove that this statement is true for staple food grains.

With that said, the aforementioned research studies also contain limitations in themselves. Therefore, their findings have to be interpreted with caution. For example, Chagwiza et al. (2016) use quantitative data from only around 400 samples. Many other studies also rely only on small sample size collected from a small area even though most of them use a very popular econometric method called Propensity Score Matching (PSM), which requires a dataset with a large sample size in order to improve its matching mechanism and accuracy (Getnet & Anullo, 2012; Hoken & Su, 2018; Ito et al., 2012; Ma & Abdulai, 2016; Verhofstadt & Maertens, 2015). Furthermore, Ainembabazi et al. (2017) assume that the decision to participate in a farmer association is random, but such an assumption is unlikely to hold because decision to join can be driven by education, knowledge, ability, or motivation to improve household income (Candemir et al., 2021). To put it another way, there is a potential selection bias. Such limitations can be another reason for the mixed evidence found in the current body of literature concerning impacts of farmer cooperatives. But to answer questions on whether or not participation in an association has positive effects on various household performance indicators requires re-investigation.

This study aims to add empirical evidence to the growing literature on the role of farmer associations by estimating their impact on farming households. We ask a simple question: Does participating in a farmer association influence household sales and crop diversification? If yes, by how much? We use one developing country, Cambodia, as our case study, and the decision to do so is based on several reasons. First, much previous research has been conducted in the context of Africa and India, but very little evidence can be found regarding the least developed countries in Asia, such as Cambodia, where some of the highest quality rice in the world is grown (Bizikova et al., 2020; Theng et al., 2014).

Secondly, unlike in many other countries, especially those comprising the Global North, in which cooperatives are highly autonomous, farmer associations in Cambodia depend largely on funding from Non-Government Organizations and tend to collapse once the funding is exhausted (Theng et al., 2014). Thus, this least developed world context is different from the contexts of countries that have been previously studied. This means that understanding just how cooperatives in least developed countries operate is crucial in determining how they may affect farming households.

The contribution of this study is threefold. First, while the vast majority of previous literature concentrates on understanding whether or not participating in cooperatives will influence farmers' income or profit, which can actually be influenced by production costs and current market price of commodities, we shift focus to sales per hectare of land and crop diversification instead. These indicators are largely overlooked (Bizikova et al., 2020) even though diversification is often reported as a crucial factor for farm sustainability (Booth & Golooba-Mutebi, 2014). Second, most research carried out in Asia or in developing countries use datasets of only a few hundred samples from a very specific area, as discussed above, but we employ the nationally representative Cambodia Inter-Censal Agricultural Survey 2019, consisting of approximately 16,000 household samples in total. This allows us to improve the accuracy of our estimation and satisfy the PSM essential requirements. Third, much of the previous literature focuses on one specific commodity such as bananas (Fischer & Qaim, 2012), apples (Ma & Abdulai, 2016), or coffee (Wollni & Zeller, 2007). We, on the other hand, use multiple valuable agro-industry crops, including aromatic rice, mango, banana, cashew nut, and cassava. It is worth noting that rice is also a typical and everyday diet for the vast majority of populations in Southeast Asian countries. Thus, this research study is also relevant to food security. To the best of our knowledge, there have been no studies using nationally representative data on the impact of farmer associations on agricultural sales and crop diversification in Southeast Asia, let alone Cambodia.

Results indicate that poorer households and those that have experienced or frequently faced natural disasters are significantly more likely to join a farmer cooperative than those who are less likely to have faced such challenges. Such findings also suggest that participation in a cooperative is a risk-sharing mechanism employed by poor rural farmers in Cambodia or that they see it as an agricultural knowledge-sharing platform that teaches them how to deal with environmental calamities. PSM outputs, in addition, indicate a significant effect of joining an agricultural organization on both sales of crop per hectare of planting area and crop diversification. For sales, the positive effects range from 11.7 to 15.7 percent while for crop diversification it is found that member households are 3.3 percent more likely to adopt commercial crops including aromatic rice, mango, banana, cassava, or cashew nut for cultivation. This effect is also strongly significant at 1 percent.

This paper is structured as follows: Following this introduction, in Section 2, we provide a theoretical background of the role of agricultural cooperatives and a synthesis of the Cambodian agricultural context. In Section 3, we discuss the data and sample that we use as well as the outcome variables. We then proceed to introduce the econometric method we employ to investigate the impact; in particular, we will talk about the Propensity Score Matching approach in Section 4. Next, results and discussion are presented in Section 5 followed by concluding remarks in Section 6.

2 Theoretical Background

2.1 Roles of Farmer Cooperatives

Farmer cooperatives have been promoted by many academics as a way to cope with various agricultural challenges in developing countries. Such thinking is based on perspectives from induced innovation theory, which insists that the most effective mechanisms to enable agricultural technology to improve productivity and meet farmer demands are farmer associations or cooperatives due to their close relationships with individual farmers (Ruttan & Hayami, 1998). These associations generally provide services to their members such as technological training as well as encouraging members to improve upon traditional farming techniques and adopt modern agricultural practices and technologies. In some cases, the associations also deliver in-kind assistance such as input for crops and livestock production although there can be contracting companies and/or supporting agencies (association partners) who are behind such training programs. Regardless, association members often have better access to fertilizer, new seeds, new markets, knowledge, and machinery compared to non-members, and that in turn tends to increase the farmers' willingness to adopt new technology. Ultimately, even the non-organized farmers are also incentivized to form a new association or join the existing one.

By forming a group and pooling their resources, individual farmers can also substantially share the production or input cost, expand their investment and operation, and hence benefit from economies of scale. Furthermore, a farmer association has been considered a good catalyst for farm commercialization between smallholders and agri-businesses (Reardon et al., 2019). For instance, smallholder farmers who participate in a cooperative can collectively sell their farm products to an agro-processor, and it is more convenient for the buyers or exporters to work with them than with non-organized cultivators. In other words, farmer associations have been an important facilitator for business transactions between farmers and potential buyers or companies. Indeed, farmer associations in Kenya, Ethiopia, and Zambia are able to export their green beans to Europe (Fischer & Qaim, 2012). On top of this, a farming cooperative can be a risk-sharing mechanism to insure against crop failure during poor harvests and to serve as a knowledge-sharing platform for disseminating best practices for disaster impact minimization and prevention. In addition, a cooperative's farmers, acting like a small-scale producers' cartel, are able to assert more control over the market and prices and improve their bargaining power in response to market failures, thus, in the end, making each member better off.

But it should be acknowledged that cartels do not normally last long. Just like firms in a cartel, each individual has an incentive to oversupply because such cheating members can reap all the benefits of additional sales but do not bear the full costs of driving the price down, which is instead shared by all members. In other words, individual members have an incentive to raise their own at the expense of that of their fellows. Some other institutional management and governance problems of large organizations also exist, including, first, heterogeneity of the farmers who have largely different interests and sometimes even deem essential changes unnecessary and, second, inefficient voting systems in which consensus for an immediate decision or cooperative strategic investment can hardly be reached on time (Candemir et al., 2021). These issues can thus prevent any attempt for reform, making the cooperatives themselves inefficient and unattractive.

2.2 Overview of the Cambodian Agriculture and Cooperatives

In the decade of 2010s, Cambodia was one of the fastest growing economies in the world, with an average growth rate of 7 percent per year while the Gross Domestic Product (GDP) per capita more than doubled, from USD 785 in 2010 to USD 1,643 in 2019 (World Bank Databank, 2021). Such remarkable development was driven by four main sectors, namely, agriculture, manufacturing, construction, and tourism. The former contributed approximately 24 percent of the country's GDP in 2018 (Royal Government of Cambodia, 2019). The importance of agriculture is also reflected in the top-level national socioeconomic development policy framework since 1994 as well as various government strategies that aim to reduce poverty, increase productivity and commercialization, and promote agro-industry and the export of agricultural products (Chhim et al., 2021).

With that said, Cambodia is still one of the developing countries in which a large majority of its agricultural labor force has continued to practice traditional rain-fed farming as its main source of income (Mishra et al., 2021). The small-scale producers or agricultural households in rural areas also face an institutionally disadvantageous situation, including limited access to potential markets, insufficient access to market information, and an unfavorable banking and insurance system (Chea, 2021). At the same time, low productivity remains one of the major challenges of Cambodia's agriculture due to an underdeveloped irrigation system and lack of agricultural knowledge among farmers regarding appropriate production techniques (Yu & Fan, 2011). These negative conditions make it very difficult for smallholder farmers and can discourage them from investing in agriculture and thus benefiting from farming. To cope with such challenges, the Cambodian Ministry of Agriculture, Forestry and Fisheries (MAFF) has, in recent years, issued five strategic plans to modernize the agricultural sector, one of which is to increase productivity, expand agrobusiness, and diversify crop production through promoting agricultural cooperatives (Chhim et al., 2021; Theng et al., 2014), which are regarded as key determinants for increasing agricultural sales. Consequently, we have seen increased crop diversification in the country even though paddy rice is still the most prevalent crop (Ofori et al., 2019).

Farmer associations in Cambodia are nothing new for rural households in the country. Small-scale agricultural associations were first formed in the 1950s and 1960s to strengthen their members' position and increase their voice and access to credit, and for that there was evidence that such cooperatives were successful, that is, until the three-decade Cambodian civil war broke out in the 1970s (ibid). But following the bloodshed, from both theoretical and legal standpoints, agricultural associations have not yet fully developed or expanded to empower farmers. And as of 2019, there were only about 130,000 farmers registered in 1,166 farming communities (Royal Government of Cambodia, 2019). The limited capacity of Cambodian agricultural cooperatives in management, marketing, and communication has been proven to be the main reason preventing them from reaching their full potential. A study by Theng et al. (2014) found that farmer organizations in Cambodia did not operate independently because most of them depended mainly on support from NGOs due to lack of capital and sustainable financing mechanisms. This might explain why the number of members of cooperatives is low in Cambodia.

Research on the effects of agricultural cooperatives in Cambodia is also extremely sparse, relying on data from small household sample sizes located in specific provinces (Ofori et al., 2019; Theng et al., 2014) and/or ruling out the possibility of selection bias (Phon & Eiji, 2016). The Cambodian government also publicly acknowledges numerous difficul-

ties in achieving its development goals, which include lack of policy-supporting research related to agriculture and agricultural technologies necessary for the government’s own decision-making process (Royal Government of Cambodia, 2019). And it is in this vein that our study also seeks to contribute to provide important insight into ongoing development efforts and evidence-based policy implications for the country.

3 Data and Outcome Variables

This study uses a dataset from the Cambodia Inter-Censal Agricultural Survey (CIAS) 2019, which is the latest nationally representative survey on agriculture in Cambodia, conducted jointly by the National Institute of Statistics, Ministry of Planning, and Ministry of Agriculture, Forestry and Fisheries. CIAS 2019 uses a sample of roughly 16,000 farm households across all 25 provinces throughout the country except for a few districts in the capital city of Phnom Penh and Preah Sihanouk Province, which are deemed highly urbanized. The survey also provides very comprehensive information about households, including their crop cultivation, livestock, aquaculture, and other agricultural activities. However, CIAS collected no village-specific data such as distance from the village to the nearest national road, seasonal movement of labour, or soil types. It should be noted that CIAS 2019 is used by the Cambodian government as a fundamental guide for formulating national strategies and policies and to monitor and evaluate the progress of agricultural development.

CIAS 2019 was conducted using a two-stage stratified sampling procedure, with Enumeration Areas (EA) as the primary sampling unit and households engaged in agriculture or farm-holdings as the secondary sampling unit (and also the unit of analysis for our study). The number of EAs to be sampled was predetermined to be 1,350 and allocated to the provinces proportionally to the number of households practicing agriculture in each province. Therefore, provinces that had many agricultural households were allocated more EAs. As for Phnom Penh, which has no rural villages, 50 EAs were allocated to it by default. For each of the 1,350 EAs, the survey team planned to randomly select 12 farm households, which would then yield 16,200 household samples. However, only 15,594 households were eventually surveyed (between June and November, 2019). National Institute of Statistics (2019) presents further details about sampling design and methodology. But not all households provided complete information about themselves. Besides, some of them did not grow any crops at all in the previous 12 months. Therefore, without complete information, which the study requires, these households had to be dropped from data analysis. Ultimately, we only used a sample of 13,327 households, 1,358 or 10.2 percent of which participated in some type of farmer organization and were thus considered as treated households or households that received treatment. The other 11,969 farm-holdings had not participated in any kind of association in the previous 12 months and were thus deemed the control or comparison group.

Table 1 highlights summary statistics of selected socioeconomic characteristics of household samples disaggregated by their participation in a farmer association. It is worth noting that the average farm size of Cambodian households is 2.5 hectares, but treated households generally hold 2.8 hectares of cultivated land areas while the non-treated or comparison groups possess a slightly less amount of 2.6. But statistically speaking, there is no significant difference in farm size between households who participate in farmer co-

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 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 of 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	-	-

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

^a observations for the treated group are 1,287 and 10,850 for the non-treated. 1,190 observations were excluded from the calculation because they did not report their land areas.

^b observations for the control are 11,968.

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

operatives and those who do not. This result, however, suggests that Cambodian farmers' amount of cultivated land is rather small, and that is consistent with findings of other studies including government figures that show that in 2017, 59 percent of Cambodian households who had agricultural land owned less than 1 hectare whereas 35 percent held between 1 and 3 hectares (National Institute of Statistics, 2017). Average household size was around four persons, remarkably lower than the same indicator in 2013, when the average household size was 4.6 (National Institute of Statistics, 2013). In addition, most households were headed by males, and only about 20 percent of all Cambodian families were female-headed, reflecting, in some sense, the structure of the society.

Other characteristics of treated and non-treated households, including age and educational level of household head and number of working adults living in the household, were what were expected and of little interest in terms of scientific knowledge. Moreover, the Mean Difference test does not suggest any remarkable variation between them. However, some notable distinctions are worth pointing out, namely, outstanding loans, engagement in agro-processing activities, experience in insect and crop diseases, engagement in cultivating commercial crops, and share of agricultural income to total income. The latter indicates that households who participated in the farmer association tended to rely more on agriculture to generate income. Their engagement in planting multiple types of commercial crops is also higher than it was for those in the control group. However, they were also more likely to experience natural disasters relative to non-organized farmers. This 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 calamity, consider the association as a method to cope with agricultural challenges. Descriptive statistics additionally show that only about 3.5 percent of total households in Cambodia are engaged in agro-processing activities, which is rather low, implying that farm-holdings are left out of the value chain. But despite the small magnitudes, notably, cooperative farmers were significantly more likely to engage in agro-processing activities than were the non-members, which is consistent with the literature discussed in Sections 1 and 2 above.

It should be noted that for the purpose of our study, we further divided the treated households into two categories, namely, those who participated in formal cooperatives officially 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). In terms of number of households, 737 households or six percent of total sample participated in a formal farmer association while 873 or seven percent participated in an informal unregistered farmer association such as farmer groups. Also of note, 252 households participated in both formal and informal cooperatives and were counted in both groups. Nevertheless, we do not report their summary statistics here, and readers are referred to appendices A-1 and A-2 for such tables.

As for the indicators used for comparison, there are two of them, which are also of interest, namely, sales and engagement in commercial crop plantation. The former is defined as total sales per hectare of all agricultural products during the previous 12 months, measured in ten thousand Riels (official Cambodian currency) while the latter is an index scale representing diversification of commercialized crops including aromatic rice, mango, banana, cashew nut, and cassava, which are considered as cash crops and used by agro-industry in Cambodia (World Bank, 2015). The index is computed using the following formula:

$$\frac{Ch - Cmin}{Cmax - Cmin}$$

where Ch is the number of commercialized crops the farm-holding is growing; $Cmax$ and $Cmin$ are the maximum and minimum numbers of commercialized crops in the sample, respectively. The scale variable has a value ranging from 0 to 1, with 1 being the most diversified. Crop diversification has been understood as a way to minimize 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 (Nguyen, 2017). In other words, diversifying crop production leads to economies of scope.

Presented in Table 2 are the differences of outcome variables between households that participated in farmer cooperatives and those that did not. The differences are disaggregated further by participation in formal or informal associations, for better understanding². Concerning the results themselves, the t-test indicates that there is no remarkable or significant difference in terms of sales of agricultural products between treated and non-treated households (Panel A). And the results are also consistent across all panels regardless of the cooperative's formal or informal status, meaning that if we compare the total amount of household sales regardless of land area each household owns, there is no significant dissimilarity among them. Nonetheless, the same statement does not hold true for sales of agriculture products per hectare of planted area. That is to say, member households are able to sell more of their cultivated products according to the amount of land they have, or simply put, if both 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. In addition, those who join associations are also more likely to adopt commercial crop cultivation. The probability is roughly 3.4 percent. But no concrete conclusion should be drawn from descriptive statistics in general, nor the t-test in particular, as such differences can be attributable to chance and can be affected by other factors. However, this provides an early indication for a more in-depth and empirical analysis. Similar results on outcome differences between households who are members of formal (Panel B) or informal farmer organizations (Panel C) and those that are not members³ are also found.

²Data on sales value are checked and cleaned, examining distribution of zero and missing and identifying gross outliers. There is plenty of outlier identification techniques. However, we use a simple univariate technique that identifies outliers as those observations that deviates from the mean more than 3.5 standard deviation. Outlier check is performed on sales value per hectare of planted area. With the outlier identification technique, we replace potential outliers by value at the upper or lower boundaries of $\bar{x} \pm 3.5 * s$, where x is mean sales value per hectare of planted area and s is standard deviation. Forty-two observations were identified as outliers and were replaced by minimum and maximum values, respectively.

³We also test a null hypothesis of no group differences on the examined outcomes between non-treated, formal and informal participation in farmer associations. The results of a one-way analysis of variance (ANOVA) are reported in Appendix A-3, and they show significant mean differences among the three groups.

Table 2: Summary Statistics of Outcome Variables by Household Participation in Farmer Associations

Variables	Obs. (treat)	Obs. (non-treat)	Mean (treated) (1)	Mean (non-treated) (2)	S.E (3)	Diff (t-test) (1)-(2)
Panel A: All Sample						
Sales (in 10 thousand riel) ^a	820	6,211	1,100.67	1,000.22	115.74	100.45
Sales per hectare of planted areas (in 10 thousand riel) ^b	798	5,741	264.58	215.47	12.73	49.11***
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 10 thousand riel)	462	6,211	1,211.27	1,000.22	151	211.05
Sales per hectare of planted areas (in 10 thousand riel)	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 10 thousand riel)	498	6,211	1,074.78	1,000.22	144.16	74.56
Sales per hectare of planted areas (in 10 thousand riel)	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***

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

^a 6,296 households (47.2 percent of the total observations) were excluded from the analysis because they did not report sales value in the past 12 months prior to survey date.

^b 6,788 households (50.9 percent of the total observations) were excluded due to similar reason as above.

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

4 Estimation Strategy

In the absence of an experimental design such as a Randomized Controlled Trial, one can never be sure that a household’s participation in the farmer cooperative is random. In fact, such participation is likely correlated with some unobservable variables such as wisdom, entrepreneurship, interest in agricultural experimentation, aspiration to improve income, and/or natural aptitude of household heads that drive them to join the association in the first place. And that means there is a selection bias. If this is the case, then we are likely to overestimate the true effects of the farm cooperative, and such effects may not be causal. That is, the correlation would be spurious. This supposition can be checked by reviewing Ofori et al. (2019) Cambodian study, which finds that cooperative members are more likely to use an irrigation system and less likely to face food security problems or perceive credit access as problematic.

Because this study uses cross-sectional data, we need to address the aforementioned challenge. And using either the Instrumental Variable (IV) method or the Propensity Score Matching (PSM) method would be a way to do so. In principle, the IV approach is preferred to PSM, for IV estimation allows one to address unobserved selection bias such as differences in motivation to participate in a farmer cooperative. However, finding a valid IV itself that is correlated with association membership but has no direct effect on outcome variables such sales is arguably very difficult if not impossible and thus empirically impractical. Therefore, this study chooses to employ PSM to investigate the causal effect of participation in farmer associations on agricultural sales of farm products and on commercialized crop diversification.

It is worth noting that the PSM method has also been used elsewhere to quantitatively evaluate the impacts of policy or program interventions if one is limited to using cross-sectional data such as in our case because it can minimize 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; Dehejia & Wahba, 2002; Rosenbaum & Rubin, 1985). Moreover, such a method is very effective and thus increasingly popular when the dataset itself comprise a sufficiently large sample size (Imbens & Wooldridge, 2009), such as the one we are using. In general, a large sample size presents a considerable advantage for matching purposes, as there is an adequate number of farm households in the comparison group, which enables common support (matched sample) and increases statistical power, thereby reducing the bias in impact estimation (Khandker et al., 2010). PSM is a two-step procedure, the first one of which involves estimating the probability that a farm household will participate in the cooperative, which is commonly known as a propensity score. The estimation itself can be done using logit (or probit) regression and can be best understood by using econometric specification as below:

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

Where subscript i indexes individual households; T is the treatment variable, which is binary and 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 take part in any kind of agricultural organization. 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; $X'\beta$ equals to $\beta_1X_1+\beta_2X_2+\dots+\beta_kX_k$ where \mathbf{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 total number of people in a household (this represents the available farm labor supply); *female* which is a dummy variable recorded as 1 if a head of a household is a female and 0 otherwise; *age*, which is the age of household head in years; *education*, which is a binary variable taking the value of 1 if household head finished high school and 0 otherwise; *dependency*, which is defined as a ratio of the number of dependents aged 0 to 14 and over 65 to adult household members aged between 15 and 64; *concrete house wall*, which is an indicator variable taking the value of 1 if a household’s wall is made of concrete and 0 otherwise (the variable is used as a proxy for household wealth in the absence of other useful asset variables); and finally *insects and crop problems*, which is a dummy variable for 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 as well as Cambodia-specific studies on the impact of farmer s on various household indicators (Abebaw & Haile, 2013; Ofori et al., 2019; Theng et al., 2014). It should be noted that we could control for socioeconomic characteristics of the community in which the households are located. However, there is no information on such covariates as a community survey was not administered.

After the model in the first step is estimated, the propensity score is predicted for every sample in the treatment and the control groups. 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 Neighbor (NN), Kernel, and Stratification. Because we have two types of treatment groups, the investigation of farmer association effects can be done by comparing groups of samples as follows:

1. Control households to households participating in a formal association (control vs. formal).
2. Control households to households participating in an informal association (control vs. informal).
3. Control households to households participating in either formal or informal associations (control vs. formal/informal).

We also check for the region of common support to avoid comparing incomparable samples, which could potentially result in a certain degree of evaluation bias. The samples whose propensity scores are not comparable (not in common support) are dropped from the data analysis. Additionally, we compare the covariates X_i before and after matching to validate the quality of our matching. This can be done using the means of absolute bias which are expected to decrease markedly after the matching. Furthermore, the standardized 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, 1983, 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 standardized bias below three or five percent after the matching should be seen as sufficient. In addition, we follow Sianesi (2004)’s suggestion to compare the Pseudo- R^2 before and after matching and that the Pseudo- R^2 before the matching

should be higher than that after the matching. In addition, the P-values of likelihood ratio tests for joint significance in the logit model should be rejected after matching, which would indicate that there are no systematic differences in the distribution of observable independent variable between both groups.

Furthermore, employing the Propensity Score Matching method requires two necessary assumptions, namely, conditional independence and common support or overlapping conditions. The former is sometimes known as the exogeneity assumption, which states that given observable independent variables, the outcome variable is independent of the intervention, or simply put, the participation in the farmer association is based entirely on observed characteristics of the household. In this regard, we can attempt to hold the conditional independence assumption valid by controlling for many observable household characteristics that can possibly affect the participation in the farmer association, as recommended by (Khandker et al., 2010). Rosenbaum and Rubin (1983) and Rosenbaum and Rubin (1985) also call this “unconfoundedness” but assert that such an assumption will hold only if appropriate common support is established. And that takes us to our second assumption, which is the overlap condition of PSM, meaning that the observations in the treatment group must have comparable doppelgangers in the control group or in the propensity score distribution. This is why data drawn from a large sample size are very much preferred, as this assumption depends almost entirely on sample size in the treatment and comparison of groups and 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.

However, with such assumptions also comes limitation, which should be properly acknowledged. Despite being a method for causal impact evaluation (Imbens & Wooldridge, 2009), PSM has a few definite drawbacks, one of which is that the approach assumes that selection bias stems mainly from observed characteristics, so it does not address the unobservable factors that might influence the probability of receiving treatment (Cerulli, 2015; Cunningham, 2021; Khandker et al., 2010). A solution would be either to include household/community covariates, which are likely to be 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, generally speaking, the Propensity Score Matching method only significantly reduces selection bias but does not eliminate it entirely. 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) and Heckman et al. (1998). First, the data on treatment and control groups are collected from the same survey using the same questionnaire by the same interviewers and during the same survey period. Second, our data come from a nationally representative survey with very large sample size, as described above. Third, the large sample size in the comparison group will smooth the matching process.

5 Result

We will now begin to answer the questions we posed at the outset, but first we need to estimate the propensity of participation in a farmer cooperative and examine the observable factors that potentially explain such participation. This can be done using a

Table 3: Probability of Participating in Farmer Cooperative (Marginal Effect)

Variables	All sample (1)	Formal (2)	Informal (3)
Household size	-0.018 (0.019)	-0.008 (0.025)	-0.036 (0.023)
Female-headed households (0/1)	-0.006 (0.071)	-0.141 (0.098)	0.077 (0.085)
Age of household head of holding	0.006 (0.028)	0.009 (0.038)	0.013 (0.034)
Age squared of household head of holding	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
Household head completed high school (0/1)	0.049 (0.098)	0.141 (0.125)	0.063 (0.119)
Dependency ratio	-0.044 (0.051)	-0.004 (0.067)	-0.062 (0.064)
House with concrete wall (0/1)	-0.187** (0.086)	-0.068 (0.110)	-0.072 (0.101)
Experience of insects and crop diseases	0.277* (0.082)	0.671* (0.096)	0.102 (0.106)
All controls	11,969	11,969	11,969
Treatment	1,358	737	873
Obs.	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
Num Of blocks	2	4	1

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

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

Stata command called *pscore* (Becker & Ichino, 2002) to estimate equation (1) above and to test the balancing property.

Table 3 presents results from the logistic regression of participation in farmer associations. We also present the marginal effect. In addition, a balancing test of all specifications was conducted, and the outputs show that balancing properties are satisfied. However, overall goodness of fit or the Pseudo R^2 is not strong. It lies somewhere between 0.001 and 0.008, but all specifications are statistically significant. As for regression results, some household-level characteristics do not seem to influence the decision to join the cooperatives. Yet this is not too unusual because Ofori et al. (2019), who conducted a somewhat similar study in Cambodia, actually arrived at the same finding, namely, that most household characteristics do not affect the choice to participate in a farmer association. In Kenya, Fischer and Qaim (2012) documented the same results. A possible explanation is that Kenyan rural households, both member and non-member of the cooperatives, have very similar socioeconomic characteristics which is proven by the Kernel density distribution of the propensity score of the treated and untreated groups before and after the matching. The Kernel density result, which is provided in Appendix B, shows that the propensity scores of both groups are relatively close. It should be emphasized also that such indication is pivotal because largely similar propensity scores will allow for a

reasonably good comparison of outcome variables. In other words, PSM will do a much better job at providing a more accurate estimation.

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

Table 4 presents 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 neighbor (column 5) (Abadie & Imbens, 2008, 2016), and we use both, for the propensity score matching does not allow for bias adjustment. Hence, we complement that by using the nearest neighbor matching approach and compare the outputs. Additionally, we perform several postestimation after-matching analyses to check 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; Roth & Tiberti, 2017). It should also be noted that we implement all these matching approaches using the *teffects psmatch* and *teffects nnmatch*, respectively, on Stata⁴ and round up the results to 3 digits.

Overall, the matching outcomes show a positive and significant impact of participation in farmer associations on both sales of crop per hectare of planted area and crop diversification. Precisely, the effects range from 11.7 to 15.7 percent for PS matching (Panel A, Column 4) or 13.7 to 15.4 percent for Nearest Neighbor matching adjusted for potential explanatory variable bias (Panel A, Column 5). Furthermore, the results are robust whether based on the number of nearest neighbor 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 if we separate the sample between those who participate in formal and informal organizations, as shown in Appendix C-1 and C-2, respectively. Other matching methods, including Kernel and Stratification, also give very similar results, so we omit them due to space limitation. In addition, we also carried out Ordinary Least Square (OLS) and fixed effect regressions to compare the results, but we do not consider such models, as the coefficients are distorted due to selection bias, as has been discussed above, even though we did control for other independent variables in the regression. Despite that, all complete results are available upon request.

In sum, our positive findings are somewhat consistent with those of Ofori et al. (2019), who found that participation in agricultural cooperatives in Cambodia does substantially

⁴There is an array of matching estimators in the literature on matching method. *psmatch2* by is one of the popular estimators (Leuven & Sianesi, 2003). Nonetheless, we choose the *teffects* over the *psmatch2* because the *teffects* considers that propensity scores are estimated rather than known when calculating standard errors.

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. (Treat)	Obs. (Matched Control)	ATET	ATET Adj.	OLS (Unmatched sample)	Diff t-test	OLS (Matched sample)	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)	0.03 (0.138)
2	820	512	0.146*** (0.05)	0.131*** (0.049)		0.034 (0.077)	0.054 (0.06)	0.149 (0.111)
3	820	757	0.136*** (0.049)	0.126*** (0.049)		0.087 (0.07)	0.071 (0.055)	0.175* (0.1)
4	820	987	0.130*** (0.049)	0.126*** (0.049)		0.134** (0.066)	0.116** (0.052)	0.253** (0.09)
5	820	1212	0.136*** (0.049)	0.125*** (0.049)	0.121**	0.140** (0.063)	0.118** (0.05)	0.227*** (0.084)
6	820	1430	0.129*** (0.049)	0.124*** (0.049)	(0.06)	0.144** (0.06)	0.108** (0.049)	0.202** (0.081)
7	820	1636	0.132*** (0.049)	0.121*** (0.049)		0.138** (0.06)	0.072 (0.05)	0.168** (0.08)
8	820	1828	0.134*** (0.063)	0.122*** (0.063)		0.144 (0.059)	0.074** (0.049)	0.174** (0.078)
9	820	2001	0.130*** (0.049)	0.128*** (0.049)		0.158*** (0.058)	0.079 (0.049)	0.176** (0.076)
10	820	2161	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	1358	329	0.033*** (0.006)	0.032*** (0.006)		0.043*** (0.012)	0.044*** (0.012)	0.047*** (0.013)
2	1358	654	0.034*** (0.006)	0.033*** (0.006)		0.039*** (0.009)	0.042*** (0.009)	0.043*** (0.013)
3	1358	971	0.034*** (0.006)	0.033*** (0.006)		0.040*** (0.007)	0.042*** (0.009)	0.043*** (0.013)
4	1358	1275	0.033*** (0.006)	0.033*** (0.006)		0.040*** (0.007)	0.044*** (0.007)	0.040*** (0.013)
5	1358	1567	0.033*** (0.006)	0.033*** (0.006)	0.033***	0.041*** (0.007)	0.045*** (0.007)	0.052*** (0.009)
6	1358	1840	0.033*** (0.006)	0.033*** (0.006)	(0.005)	0.041*** (0.006)	0.044*** (0.007)	0.041*** (0.013)
7	1358	2106	0.033*** (0.006)	0.033*** (0.006)		0.040*** (0.006)	0.044*** (0.006)	0.034*** (0.013)
8	1358	2362	0.033*** (0.006)	0.033*** (0.006)		0.041*** (0.006)	0.045*** (0.006)	0.050*** (0.013)
9	1358	2609	0.033*** (0.006)	0.033*** (0.006)		0.040*** (0.005)	0.044*** (0.006)	0.027*** (0.013)
10	1358	2853	0.033*** (0.006)	0.033*** (0.006)		0.040*** (0.005)	0.043*** (0.006)	0.036*** (0.013)

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

Note: ATET is the average treatment effect on the treated, whereas ATET Adj. is the ATET adjusted for biases of the covariates. Given that sales value is in logarithmic form, resulting in a semilogarithmic estimation, we interpret the coefficient using $\% \Delta \beta = (e^\beta - 1) * 100$. Standard errors are in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1.

impact farm revenue. Simply put, member households can sell more of their cultivated products than can 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 a finding would include the dissemination of information on agricultural technology, which increases productivity (Zhang et al., 2020), and the improvement of 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 group of producers (Grashuis & Magnier, 2018). And as the producer theory predicts, product differentiation leads to higher sales and incomes.

Apart from that, 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-percent more likely to adopt commercial crops like aromatic rice, mango, banana, cassava, or cashew nuts for plantation. The effect is statistically significant even at 1 percent. Similar gains are also observed for farming households that participate in either formal or informal farmer organizations (Appendix C-1 and C-2, Panel B). Again, the results can be attributable to the members’ improvement in technical efficiency, as has been 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 the country’s cooperatives, besides providing a risk-sharing mechanism, also behave like a knowledge-sharing platform for farmers, which is why those who had experienced natural disasters in the previous 12 months were more likely to join an association to learn workaround methods to minimize the damage done by such catastrophes.

6 Concluding Remark

Using the Propensity Score Matching approach, this study investigates the impact of farmer associations on agricultural sales per hectare of planted area and crop diversification, the two indicators that are largely overlooked in the literature. Unlike most previous studies, which tend to rely on small sample sizes and/or focus on a specific crop, we employ the Cambodia Inter-Censal Agricultural Survey 2019, which gathered roughly 16,000 farm-holding samples 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 is able to utilize such data and outcome variables. As a result, our study contributes to the field not only new and strong empirical evidence on the influence of farmer cooperatives on various household performance indicators but also represents much potential in terms of offering Cambodian policymakers applicable knowledge and evidence-based policy implications to help farmers and their communities to acquire better agricultural insight and thereby achieve the goals set in the Cambodia National Strategic Development Plan (NSDP) 2019–2023, which emphasizes the expansion of the agricultural sector as well as meeting the Sustainable Development Goals. In particular, Goal 1 (end all forms of poverty) and Goal 2 (end hunger, achieve food security, improve nutrition, double agricultural product, and promote sustainable food production).

Findings show that many rural households see cooperatives as a risk-sharing strategy and that member households do indeed benefit from participating in such organizations 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 are able to learn of the advantages of diversifying and of the advantages of the crops they should grow, as well as being given the input to do so, including seeds and/or technology. However, we cannot clearly understand through which mechanism that cooperatives influence crop diversification, but the effect on sales is more likely to stem from the increasing market and bargaining power and information about potential markets. It should also be noted that even though there are positive effects on both outcomes, we are unsure if the gain from membership is practically big or small because we did not conduct a cost-and-benefit analysis. That is to say, we could not fully understand if farming households are economically benefiting from the membership, for they are required to pay membership fees or contribute in the form of in-cash or in-kind to the operations of the cooperatives. Economically speaking, the monetary benefits from the membership could be smaller compared to direct and opportunity costs they incur. This can be a topic for future research.

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, a financing model that can help sustain the cooperatives is crucial now for their survival, but both governance and financial management of associations should be autonomous and able to cut through unnecessary and time-consuming paperwork in order to overcome bureaucratic frustration. The government can also play a big role in helping establish, improving, and supporting cooperatives by providing technical assistance, including on how to set up a local cooperative, as well as other crucial training on management, farming technologies, and know-how.

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APPENDIX

Appendix A-1: Summary Statistics of Selected Socioeconomic Characteristics (formal)

Variables	Mean (treated) (1)	Mean (non-treated) (2)	<i>S.E</i> (3)	<i>Diff</i> (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 ^{***}
<i>Obs.</i>	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)	<i>S.E</i> (3)	<i>Diff</i> (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***
<i>Obs.</i>	873	11,969		

Source: Authors' calculations using Cambodia Inter-Censal 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.

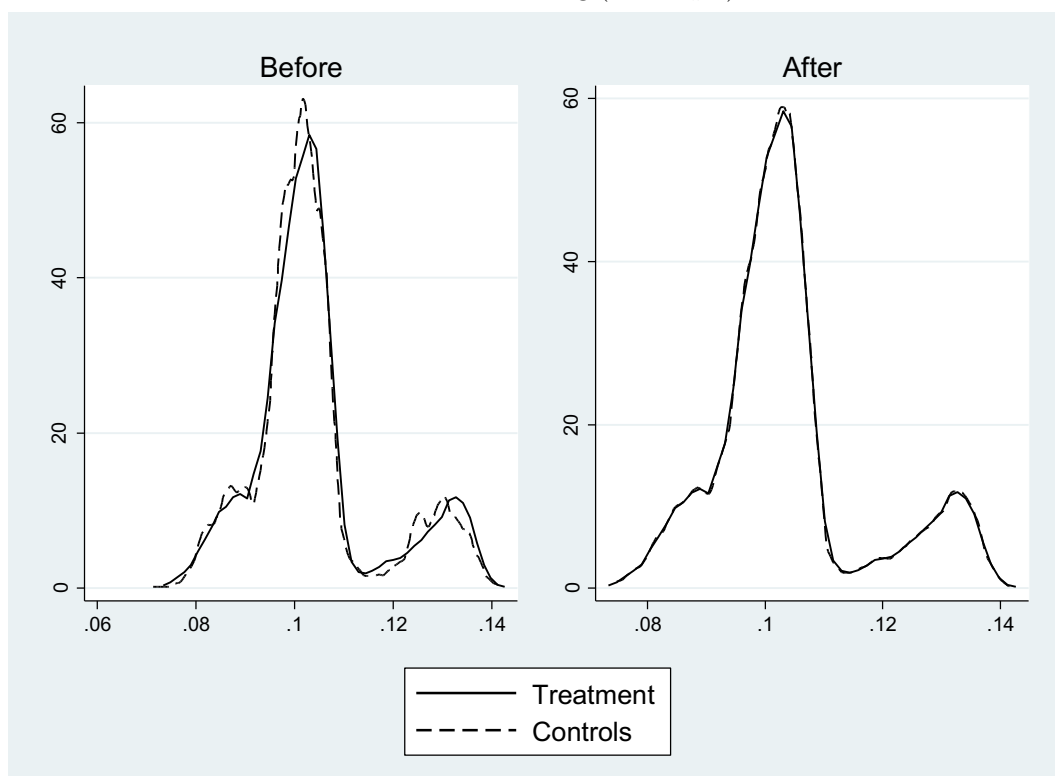
Appendix A-3: One-Way Analysis of Variance

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

Source: Authors' calculations using Cambodia Inter-Censal 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)



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

Appendix C-1: The Effect of Participation in Farmer Cooperatives on Sales and Engagement in Commercial Crop Plantation (formal)

<i>n</i>	<i>Obs.</i>			ATET	ATET Adj.	OLS (Unmatched sample)	Matched sample		
	Treated	Matched Controls					<i>Diff</i> 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 (0.117)	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)	0.112* (0.060)	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)		0.030** (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)	0.027*** (0.006)	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)	

(0.007) (0.007) _____ (0.007) (0.007) (0.014)

Source: Authors' calculations using Cambodia Inter-Censal 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)

<i>n</i>	<i>Obs.</i>		ATET	ATET Adj.	OLS (Unmatched sample)	Matched sample		
	Treated	Matched Controls				<i>Diff</i> 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 ^{***}	0.193 ^{**} (0.076)	0.151 ^{**} (0.064)	0.279 ^{***} (0.091)
6	484	1,109	0.176 ^{***} (0.063)	0.180 ^{***} (0.063)	(0.058)	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 ^{***} (0.087)
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 ^{***}	0.035 ^{***} (0.007)	0.039 ^{***} (0.008)	0.030 ^{***} (0.014)
6	873	1,557	0.027 ^{***} (0.007)	0.026 ^{***} (0.007)	(0.006)	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 ^{***} (0.014)

(0.007) (0.007) _____ (0.007) (0.007) (0.015)

Source: Authors' calculations using Cambodia Inter-Censal 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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.