Agricultural cooperatives, Good Agricultural Practice (GAP) standard, Main Crop Equivalent Yield (MCEY) and farm profit: Evidence from a country-wide agricultural survey in Cambodia

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18 July 2025
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Abstract

Enhancing agricultural productivity and commercialisation among small-scale farmers has been widely viewed as a key policy objective for rural development, poverty reduction and food security in developing countries. At the same time of dealing with production challenges, there is a growing concern that small-scale farmers also face challenges in complying with stringent food standards to respond to the increasing demand for higher-quality and safer food products. Cambodia introduced regulatory legislation on Good Agricultural Practices standard (CamGAP), contracting farming (CF) and agricultural cooperatives (ACs) in 2010, 2011 and 2013, respectively, to support smallholders to overcome the challenges. However, little is known about the impact of such policy support on small-scale farmers. Previous studies highlighted the impact of each intervention, while the impact of the simultaneous intervention of CamGAP and ACs through CF schemes remained limited in the literature. This study aims to examine the heterogeneous impact of AC membership and CamGAP adoption on farm outcomes. We used the most recent country-wide survey data, allowing the study to account for all crops grown by farmers' households in Cambodia. Because rice remained a major crop in the country, we computed Rice Equivalent Yield (REY) to measure farm yield and meaningful farm profit. To effectively mitigate the concerns of endogeneity, we employed Inverse Probability Weighting with Regression Adjustment (IPWRA) to estimate the impact, while Endogenous Switching Regression (ESR) was used for robustness checks. Without distinguishing AC members by CamGAP adoption, the findings are consistent with the growing empirical literature that AC membership statistically significantly improved farm outcomes. By separating the distinct groups of AC members under the condition of CamGAP adoption, we found that AC membership significantly improved farm outcomes only when CamGAP was adopted. AC members who did not adopt CamGAP did not achieve better farm outcomes compared to non-members. AC members who adopted CamGAP received statistically and significantly higher REY and farm profit compared to non-members. AC members who adopted CamGAP obtained 1.09 tons per hectare of REY and 1.08 million riels (USD270) of farm profit per year, higher than AC members who did not adopt CamGAP. These findings suggest the significant role of integrating food standard certification in ACs.

Keywords: Good Agricultural Practice Standard, Contract Farming, Agricultural Cooperatives, Rice Equivalent Yield (REY), Farm Profit, Inverse Probability Weighting with Regression Adjustment, Endogenous Switching Regression

1. Introduction

Enhancing agricultural productivity and commercialisation among small-scale farmers has been widely viewed as a key policy objective for rural development, poverty reduction and food security in developing countries. At the same time of dealing with production challenges, there is a growing concern that small-scale farmers also face challenges in complying with stringent food standards to respond to the increasing demand for higher-quality and safer food products (Barrett et al., 2002; Narrod et al., 2009; Reardon et al., 2008). Relevant to these issues, in Cambodia, the government introduced a local agricultural production standard called Cambodia Good Agricultural Practice (CamGAP) in 2010 by adopting a regional standard, namely ASEAN GAP. In the following years, a sub-decree on contract farming (CFs) and a law on agricultural cooperatives (ACs) were also enacted in 2011 and 2013, respectively, to provide farmers with more support to overcome the challenges. Since then, AC members have been targeted as participants of training series on agricultural techniques, e.g., soil management, water management, integrated pest management (IPM) and record keeping to comply with CamGAP (ADB, 2023; Department of Plant Protection Sanitary and Phytosanitary, 2020; Kuy, 2024; Onjeonhi, 2025). The progressive effort from policies and development partners suggests a strong relationship between ACs, CFs and CamGAP in improving smallholders' performance in Cambodia's context. However, despite a decade of policy support, the integration between ACs, CFs and CamGAP remained in pilot projects in the country. Only 16% of ACs in Cambodia were linked to CFs (Ngo & Khon, 2023), suggesting a limitation in access to CamGAP certification that would lead to heterogeneous farm outcomes among AC members.

Contemporarily, a growing body of empirical studies have only highlighted the impact of AC membership on farm outcomes in various countries, leaving a limited understanding of the differences in farm outcomes between ACs adopting food standards and those following conventional production. A group of empirical results revealed that AC membership statistically significantly improved the farming technical efficiency (Abdul-Rahaman & Abdulai, 2018; Lin et al., 2023; Ma et al., 2018), yield (Lin et al., 2022; Ma et al., 2022) and income (Wu et al., 2023). This literature group did not lay out a food standard among AC members in their studies. Because of this, the impact of the AC membership they reported remained broad, limiting insight into the heterogeneous impacts, which are crucial for policy implications. In developing countries where CFs and local food standard certification have been promoted, ACs could be distinguished into distinct groups under the condition of the treatment. Taking the food standard issue into consideration, Ma and Abdulai (2018) highlighted the improvement of apple yield among AC members who adopted IPM. However, the study only partially addressed whether food standard adoption among AC members statistically improved farm outcomes. It is because GAP certification demands a more comprehensive approach to farm production and management beyond the IPM adoption (Annor et al., 2023; FAO, 2003).

In relation to farm outcomes, previous studies made conclusions about the impact of AC membership based on a sample of single crops. For example, coffee was studied in Costa Rica (Wollni & Zeller, 2007), Ethiopia (Shumeta & D'Haese, 2016) and Peru (Grashuis & Skevas, 2023), watermelon in China (Ito et al., 2012), apple in China (Hao et al., 2018; Ma & Abdulai, 2016, 2017; Ma et al., 2018), rice in China (Hoken & Su, 2018; Lin et al., 2022), Ghana (Abdul-

Rahaman & Abdulai, 2018; Addai et al., 2022), Bangladesh (Bairagi & Khondoker Abdul, 2021) and Vietnam (Tran et al., 2022), potato in Mongolia (Ahado et al., 2021), maize in Nigeria (Olagunju et al., 2021) and Ethiopia (Geffersa, 2024a, 2024b), banana in China (Ma et al., 2022; Zhou et al., 2024), and tobacco in China (Lin et al., 2023). However, smallholders in developing countries, e.g., Cambodia, often grow multiple crops throughout the year, e.g., rice, maize, cassava, cashew, etc. (NIS, 2024). Different crops can be grown on different farms or the same farms in different seasons, rather than only the crops that ACs focus on. At the same time, some farmers may have diversified their crops to the one promoted by ACs. Thus, the establishment of ACs when the CFs and CamGAP have been integrated may have created a mixture of practices that can influence aggregate farm outcomes per year from the limited farm sizes that smallholders own.

This study aims to contribute to the literature by shedding light on the heterogeneous effects of joint AC membership and CamGAP adoption on farm outcomes. The analysis examines the role of CamGAP in catalysing the improvement of AC members' farm outcomes. It is vitally beneficial for policymakers to understand whether they should promote CamGAP to ACs that have not yet put CamGAP in their business strategies. It is because diversifying conventional production into CamGAP-certified production may require a higher investment to comply with contracts agreed with the downstream actors (e.g., food processors, supermarkets, etc.). To provide an accurate insight into the heterogeneous impact, this study distinguishes farmers into three distinct groups: 1) AC members who adopted CamGAP, 2) AC members who did not adopt CamGAP and 3) non-members, while the previous studies only compared AC members to non-members (e.g., Geffersa (2024a); Ma et al. (2022); Tran et al. (2022)). Another contribution is that this study accounts for all crops and farming systems available in a country-wide survey data (presented in Section 2.1).

Figure 1.1 presents the conceptual framework of this study. In developing countries, production can be driven by buyers through the higher structures of the value chain governance that require a higher degree of asset specification (e.g., specific inputs, farm maintenance procedures) as implied by the transaction cost theory (Williamson, 1979). Downstream actors such as processors, wholesalers and retailers (supermarkets) tend to be interested in offering contracts to ACs to lower transaction costs compared to individual farmers (Barrett et al., 2012; Reardon et al., 2009; Tray et al., 2021). This implies a strong relationship between ACs and CFs. The contractual relationship between downstream actors and ACs can provide smallholders a better opportunity to access high-value markets. This allows stallholders to enhance their capacity to deal with the increasing demand for higher-quality and safer food through a training series to comply with required standards. Recently, Annor et al. (2023) revealed a significantly statistically positive relationship between AC membership and food standard adoption. To comply with food standard certification, farmers are required to invest in other facilities beyond production inputs (Annor et al., 2023). In this study, however, we only account for input expenditure that determines farm outcomes (productivity and profit).

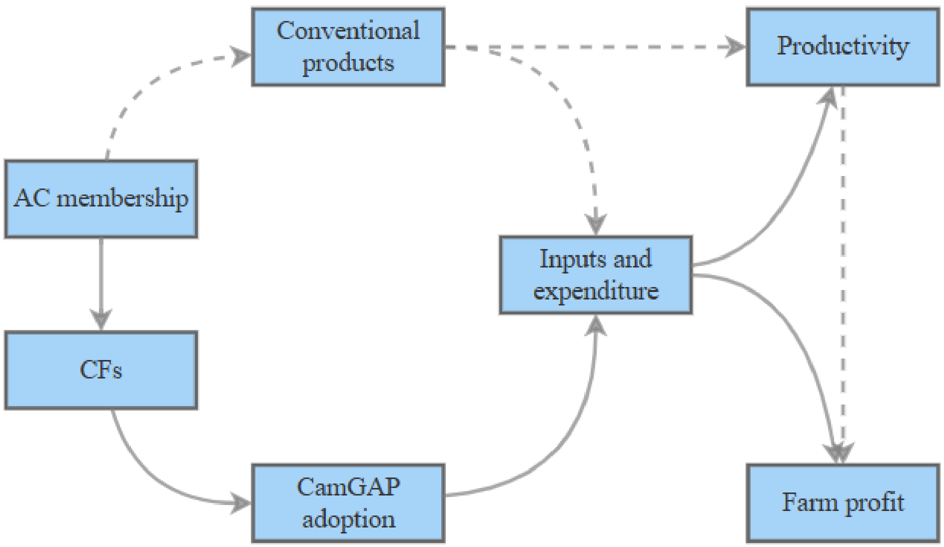

Figure 1.1 Conceptual framework

Section 2 presents data, outcome computations and empirical methods selected to estimate the impact of AC membership on the farm outcomes, along with methods used for robustness checks. Section 3 illustrates the empirical results and robustness checks, while Section 4 concludes the study along with the study limitations and policy implications.

2. Data, outcome computations and empirical analysis

2.1 Data and outcome computations

This study used the latest country-wide Cambodia Agricultural Survey 2023 (CAS2023). The survey was conducted during November and December 2023. The data comprises 15,292 agricultural households from all provinces (25) across the country. This study included only crop-producing households, resulting in the final sample of 10,003 valid cases. In this study, we estimate the heterogeneity of the impact of AC membership on farm yield and farm profit under the condition of CamGAP adaptation. The dataset contains 47 crops. When accounting for all crops produced by the sampled households, we need to consider the issue of different input uses (investment) and different yields due to the nature of distinct crops. Different crops also have different prices. Because of this, the measurement for this quantification becomes a demanding task at the initial stage of outcome computation in this study, compared to studies in the field, which accounted for only one crop, e.g., Lin et al. (2022); Ma et al. (2022); Tran et al. (2022). To measure the average farm yield achieved by the sampled crop-growing households from certain planted areas with various numbers of harvests per annum, we adopted Assefa et al. (2023) to compute major crop equivalent yield (MCEY). Rice remained a major crop in Cambodia (ADB, 2021), so we computed rice equivalent yield (REY) as a farm yield measurement. REY can be computed using Equation (1).

$$REY_i = Q_{iRice} + \left(\frac{Q_{ij=a} \times P_{ij=a}}{P_{iRice}}\right) + \left(\frac{Q_{ij=b} \times P_{ij=b}}{P_{iRice}}\right) + \left(\frac{Q_{ij=c} \times P_{ij=c}}{P_{iRice}}\right) + \cdots + \left(\frac{Q_{ij=z} \times P_{ij=z}}{P_{iRice}}\right). \quad (1)$$

where REY_i is the rice equivalent yield in kilograms per hectare (kg/ha) accounted for all crops produced by the household i per annum; $Q_{iRice}$and P_{iRice} were already defined above. $Q_{ij=a,b,c,\dots z}$ refers to the quantity of crops $a, b, c, \dots, z$ in kg/ha per annum. $P_{ij=a,b,c,\dots,z}$ refers to the actual price of crops $a, b, c, \dots, z$. The available structure of the data suggests that we need to account for the certain plots (f) and certain harvest (h) for certain crop types (j). To compute REY, we require four main variables: a) Quantity of rice Q_{Rice} harvested by household i, hereafter denoted as Q_{iRice}, b) Price of rice achieved by household i (P_{iRice}), c) Quantity of crop j harvested by household i and d) Price of crop j achieved by household i. The annual quantity of certain crops can be written as $Q_{ij} = \sum_{ij,f=1}^{k} \sum_{ijf,h=1}^{k} \left(\frac{Q_{ijfh}}{fs}\right)$.

The farm profit can be computed using Equation (2).

$$Farm\,profit = \left(\sum_{ij=a}^{z} Q_{ij}\right) - \left(\sum_{ij=a}^{z} V_{ij}\right). \tag{2}$$

where Q_{ij} was already defined above; V_{ij} is variable expenditure, including fertilisers, pesticides, seeds, opportunity cost for household labour, and opportunity cost for owned seed quantity used for farming. $\left(\sum_{ij=a}^{z} Q_{ij}\right)$ is the gross revenue from all crops harvested by the household i. $\left(\sum_{ij=a}^{z} V_{ij}\right)$ is the total key input expenditure per annum for the household i invested in growing all crops.

2.2 Empirical analysis

Using cross-sectional data for impact assessments, contemporary literature in the field employed three methods: 1) Propensity Score Matching (PSM) (e.g., Fischer & Qaim, 2012), 2) Inverse Probability Weighting with Regression Adjustment (IPWRA) (e.g., Liu et al., 2018) and Endogenous Switching Regression (ESR) (e.g., Ma et al., 2022; Wu et al., 2023). The PSM estimate is prone to selection bias because the method fails to account for unobservable factors. The IPWRA and ESR are powerful methods to deal with endogeneity. The IPWRA uses Inverse Propensity Weights, and the ESR uses Inverse Mills Ratio to remove the concerns for endogeneity. Because of this, we used the IPWRA to estimate the heterogeneous impact of AC membership on the farm outcomes and the ESR for robustness checks.

In this study, the IPWRA is estimated in four steps. Firstly, we estimate propensity scores using a probit model accounting for observable variables as the first step in the PSM method. Unlike the PSM, which samples only cases with similar characteristics based on the propensity scores, the IPWRA includes all cases without a matching procedure. Secondly, instead of matching, the propensity scores are converted into weights. Third, we use weighted least squares (WLS) to estimate the outcomes, accounting for the inverse propensity weights to address the selection bias. In this step, we estimate two different outcome regressions: 1) AC members and AC members and 2) non-members, to examine the broad impact of AC membership similar to the empirical literature (e.g., Ma et al., 2022; Wu et al., 2023). To obtain more accurate insights, this study attempts to capture the heterogeneous impact of the simultaneous double/joint treatments: AC membership and CamGAP. To achieve this, it is reasonable to estimate two more outcome regressions: one for AC members adopting CamGAP and one for AC members without adopting CamGAP. The last step (four) is the causal inference analysis to estimate the heterogeneous impact. We compare the mean predicted outcomes across the subsets of interest.

The probit model to estimate the propensity scores can be written as

$$AC = \alpha_0 + \alpha_1 X_1 + \alpha_2 X_2 + \cdots + \alpha_k X_k + e_1 \tag{3}$$

where, AC is a 'treatment' dummy variable that scores 1 if the household holds an AC membership, and 0 otherwise α_0; to α_k are parameters to be estimated and e_1 is a random error.

The propensity scores are converted into weights to be accounted for in the outcome regressions using three different subsets as presented in Table 2.1.

Table 2.1 The matrix of outcome regressions using WLS can be arranged into four pairs.

Impact of broad treatment (n1)		Impact of double treatment (n2)		Impact of single treatment (n3)		Comparison between double and single (n4)	
$\beta_1 \mid AC=1$	$\beta_0 \mid AC=0$	$\beta_1 \mid AC = 1\ \&\ GAP=1$	$\beta_0 \mid AC = 0$	$\beta_1 \mid AC = 1\ \&\ GAP=0$	$\beta_0 \mid AC=0$	$\beta_1 \mid AC = 1\ \&\ GAP=1$	$\beta_1 \mid AC = 1\ \&\ GAP=0$
$\beta_2 \mid AC=1$	$\beta_2 \mid AC=0$	$\beta_2 \mid AC = 1\ \&\ GAP=1$	$\beta_2 \mid AC = 0$	$\beta_2 \mid AC = 1\ \&\ GAP=0$	$\beta_2 \mid AC=0$	$\beta_2 \mid AC = 1\ \&\ GAP=1$	$\beta_2 \mid AC = 1\ \&\ GAP=0$
…………	…………	…………	…………	…………	…………	…………	…………
$\beta_k \mid AC=1$	$\beta_k \mid AC=1$	$\beta_k \mid AC = 1\ \&\ GAP=1$	$\beta_k \mid AC = 1$	$\beta_k \mid AC = 1\ \&\ GAP=0$	$\beta_k \mid AC=1$	$\beta_k \mid AC = 1\ \&\ GAP=1$	$\beta_k \mid AC = 1\ \&\ GAP=0$
E[$\hat{Y}$|AC=1]	E[$\hat{Y}$AC=0]	$\mathrm{E}[\hat{Y} \mid AC = 1\ \&\ GAP = 1]$	E[$\hat{Y}$|AC=0]	$\mathrm{E}[\hat{Y} \mid AC = 1\ \&\ GAP = 0]$	E[$\hat{Y}$|AC=0]	$\mathrm{E}[\hat{Y} \mid AC = 1\ \&\ GAP = 1]$	$\mathrm{E}[\hat{Y} \mid AC = 1\ \&\ GAP = 0]$
$\mathrm{ATE} = \mathrm{E}[\hat{Y} \mid \mathrm{AC} = 1] - \mathrm{E}[\hat{Y} \mid \mathrm{AC} = 0]$		$\mathrm{ATE} = \mathrm{E}[\hat{Y} \mid AC = 1\ \&\ GAP = 1] - \mathrm{E}[\mathrm{Y} \mid \mathrm{AC} = 0]$		$\mathrm{ATE} = \mathrm{E}[\hat{Y} \mid AC = 1\ \&\ GAP = 0] - \mathrm{E}[\mathrm{Y} \mid \mathrm{AC} = 0]$		$\mathrm{ATE} = \mathrm{E}[\hat{Y} \mid AC = 1\ \&\ GAP = 1] - \mathrm{E}[\hat{Y} \mid AC = 1\ \&\ GAP = 0]$	

where β_0 to β_k are regression coefficients estimated by WLS; n1 is the full sample without interest in CamGAP; n2 is the subset containing members who adopted CamGAP and non-members, excluding members who did not adopt CamGAP; n3 is the subset containing members who did not adopt CamGAP and non-members, excluding members who adopted CamGAP; n4 is the subset containing members who did not adopt CamGAP and members who adopted CamGAP, excluding non-members. ATE is Average Treatment Effects; $\mathrm{E}[\hat{Y} \mid \mathrm{AC} = 1]$ is the mean predicted outcome for AC members; $\mathrm{E}[\hat{Y} \mid \mathrm{AC} = 0]$ is the mean predicted outcome for non-members; $\mathrm{E}[\hat{Y} \mid AC = 1\ \&\ GAP = 1]$ is the mean predicted outcome for AC members who adopted GAP; $\mathrm{E}[\hat{Y} \mid AC = 1\ \&\ GAP = 0]$ is the mean predicted outcome for AC members who did not adopt GAP.

It is noticeable that we use only one selection model using the full sample (n1). It is because we assume that CamGAP is the additional layer of treatment to ACs. From policy perspectives, in a small economy like Cambodia, which is dominated by small-scale farmers, downstream actors seek opportunities to work with farm groups who are ready for collective action, rather than individual farmers, due to the perception of transaction costs (Narrod et al., 2009). In this sense, CamGAP supporting programs tend to work with ACs where CF schemes are active. Thus, this can be assumed that CamGAP is not involved in farmers' decisions.

This study uses the ESR to check robustness. The ESR estimation involves three steps. Firstly, we estimate the probit selection regression, which is identical to Equation (3), except for the inclusion of instrumental variables. This study uses crop diversification as an instrumental variable. Before proceeding with other estimation stages, we adopte Stock and Yogo (2003) to use the Cragg-Donald F-statistic and the Stock-Yogo test to validate that the IV is acceptable. We then compute the Inverse Mills Ratio (IMR) from the first-stage probit. Secondly, we regress outcome regressions. Unlike the IPWRA, which accounts for inverse propensity-score weights in the outcome regressions using WLS, the ESR accounts for IMR in the outcome regressions using Ordinary Least Squares (OLS). Additionally, the Variance Inflation Factor (VIF) is used in all regression models in this study to test that the models are free from multicollinearity issues. The third step is to compare the mean predicted outcomes, which are the average treatment effects (ATEs) across the four pairs of comparison groups to capture the heterogeneous effects. In this study, the ESR outcome regression estimates and ATEs are also presented in the sample matrix as shown in Table 2.1.

3. Findings and discussion

3.1 Variables included in the empirical analysis

Table 3.1 presents the definition of variables and their statistics (mean and SE). The data contains approximately 4% of households that have participated in ACs. This participation rate was about 1% higher than that sampled by CAS2021 (NIS, 2024). The mean REY was 3.34 tons per hectare, consistent with the estimate of 3.35 tons per hectare of paddy yield reported by (FAOSTAT, 2025). The mean REY computed from CAS2023 was higher than that computed from CAS2021, which was only 2.97 tons per hectare. The mean farm profit was 1.88 million riels, 1.11 million riels higher than that computed using CAS2021 data. The mean expenditure on key inputs was 1.76 million riels per hectare, 0.63 million riels higher than that computed using CAS2021 data. Along with the increase in REY, profit and expenditure compared to the 2021 data, the mean planted area also increased to 2.22 hectares in 2023 from 1.58 hectares in 2021. The increase in planted areas from 2021 justifies that the increase in REY and farm profit is reasonable.

The sampled households owned 0.97 hectares of farmland per capita (household members within the age range of 18-64 years old). Only 34% of them used irrigation for crop farming. Most households (77%) were male-headed, and they had around 5 members on average. Approximately 2 household members had at least a secondary education. The sampled households grew one crop, indicating that they focused on a certain crop type in 2023. In 2021, according to CAS2021 (NIS, 2024), Cambodian farmers grew 2 crops on average. The mean distance between their dwelling and the market for farm output was approximately 1.83 kilometres. Only 35% of the sampled households had their own means of transporting their farm outputs. The majority of households (92%) produced rice, while only 43% produced cassava. The percentage of rice and cassava producing households is consistent with that computed from CAS2021 data. We included the dummy variables: Rice and Cassava, because these crops received policy support in 2010 and 2018, respectively, in Cambodia (CoM, 2010, 2015, 2020; MoC, 2019).

Table 3.1 Variable definitions and statistics

Variable	Definition	n	Mean	SE
Treated variable				
AC	1=Member of a registered agricultural marketing cooperative, 0 otherwise	10,003	0.038	0.002
Outcome variables				
REY	Rice equivalent yield (tons/ha)	10,003	3.335	0.024
Profit	Farm profit (million riels)	10,003	1.876	0.027
Explanatory variables				
Expenditure	Total expenditure for crop farming per annum (million riels)	10,003	1.761	0.019
Planted area	Total area planted to crops (ha)	10,003	2.223	0.036
Farmland	Farmland endowment (ha per adult equivalent)	9,971	0.969	0.032
Irrigation	1=Used irrigation, 0 otherwise	9,990	0.344	0.005
Gender	1=Male-headed household, 0 otherwise	10,003	0.770	0.004
Hhld size	Number of people in the household (#)	10,003	4.826	0.019
Education	Number of household members with at least secondary schooling (#)	10,003	1.601	0.013
Crops	Number of crops grown (#)	10,003	1.104	0.003
Distance	Distance from dwelling to market (km)	10,003	1.830	0.025
Transport	1=Own transport means including tillers, tractors or trucks for transporting farm outputs, 0 otherwise	10,003	0.354	0.005
Rice	1=Rice producing households, 0 otherwise	10,003	0.922	0.003
Cassava	1=Cassava producing households, 0 otherwise	10,003	0.043	0.002

Table 3.2 compares characteristics of AC members and non-members. AC members achieved 3.70 tons per hectare of REY, 0.38 tons higher than non-members. AC members also obtained higher farm profits compared to non-members by 0.50 million riels (USD125) from crop production per year. However, the t-test estimates are prone to bias because they do not account for both observable and unobservable variables. Preliminarily, we also compared the mean explanatory variables between the two groups. Seven out of twelve variables were statistically significant, encompassing Expenditure, Planted area, Gender, Hhld size, Crops, Distance and Transport. Despite the statistical insignificance, we retain variables: Farmland, Irrigation, Rice and Cassava because they have explanatory power in empirical analysis.

Table 3.2 Differences in characteristics of AC members and non-members

Variable	Members			Non-members			Difference
	n	Mean	SE	n	Mean	SE	
REY	380	3.700	0.144	9,623	3.321	0.024	0.379**
Profit	380	2.257	0.169	9,623	1.861	0.027	0.396**
Expenditure	380	2.312	0.129	9,623	1.739	0.019	0.573***
Planted area	380	3.511	0.224	9,623	2.172	0.036	1.339***
Farmland	378	1.137	0.120	9,593	0.963	0.033	0.174
Irrigation	380	0.339	0.024	9,610	0.344	0.005	-0.004
Gender	380	0.821	0.020	9,623	0.768	0.004	0.053***
Hhld_size	380	5.279	0.094	9,623	4.808	0.020	0.471***
Education	380	1.721	0.070	9,623	1.596	0.014	0.125
Crops	380	1.219	0.022	9,623	1.099	0.003	0.120***
Distance	380	2.788	0.253	9,623	1.792	0.024	0.995***
Transport	380	0.526	0.026	9,623	0.347	0.005	0.179***
Rice	380	0.939	0.012	9,623	0.921	0.003	0.019
Cassava	380	0.047	0.011	9,623	0.043	0.002	0.005

** p < 0.05, *** p < 0.01

3.2 Determinants of AC membership

Table 3.3 presents the estimate of the probit selection model. The Chi-squares (χ2) statistic shows that the estimated model has explanatory power. The VIFs are close to unity, indicating that the parameter estimates are free of multicollinearity bias. Farmers with larger household sizes are more likely to participate in ACs. This result is consistent with previous studies (e.g., Abate et al., 2014; Ma et al., 2022). Distance was also a factor influencing the decision to be AC members. This finding is similar to that of Abebaw and Haile (2013). Farmers owning means of transportation also had a positive relationship with AC membership, implying that transportation enhances economic participation, mobility and logistical efficiency, making AC membership an attractive option for a certain group with this attribute.

Table 4.3 Determinants of AC membership estimated by the probit model

Variable	Estimate	Marginal Effect	SE	VIF
Farmland	0.003	0.001	0.007	1.008
Irrigation	0.041	0.010	0.050	1.021
Gender	0.070	0.017	0.060	1.026
Hhld size	0.053***	0.013	0.014	1.233
Education	0.003	0.001	0.019	1.232
Distance	0.036***	0.009	0.007	1.023
Transport	0.290***	0.072	0.048	1.017
(Intercept)	-2.317***		0.085	
n	9958			
Log Likelihood	-1558.47			
F-statistic	$14.01^{***}_{7,9951}$			
χ^2 (7) Statistic	51.00			
P (> χ^2)	0.0000			

** p < 0.05, *** p < 0.01

3.3 Heterogeneous impact of AC membership on REY

Table 3.4 presents outcome regressions estimated using WLS for REY, accounting for inverse propensity weights computed from the estimated propensity scores in Table 3.3. Table 3.5 provides ESR estimates for the robustness checks of the REY estimates. The outcome regression estimates are arranged into four pairs. We found consistent results between the application of the IPWRA and ESR. The findings reveal that under the condition that CamGAP is not included in the model, AC membership improved REY by 0.33 tons per hectare. Without taking account into CamGAP, this finding is consistent with empirical evidence from other countries (e.g., Abdul-Rahaman & Abdulai, 2018; Lin et al., 2022; Ma et al., 2022). Interestingly, in contribution to the literature, we found that AC membership could improve REY only under the condition that ACs adopt CamGAP. REY achieved by AC members who adopted CamGAP was statistically significantly higher than non-members by 1.07 tons per hectare, while there was no statistically significant difference between REY achieved by AC members who did not adopt CamGAP and non-members. Additionally, the findings clearly distinguished between members adopting CamGAP and members who did not adopt CamGAP, as those who adopted CamGAP obtained REY 1.09 tons per hectare higher than members who did not adopt CamGAP.

Table 3.4 IPWRA outcome regression estimating REY

Explanatory variable	Full sample (n1)		ACs with GAP (n2)		ACs without GAP (n3)		Adopters vs non-adopters (n4)	
	Members	Non-members	Mem GAP	Non-members	Mem non GAP	Non-members	Mem GAP	Mem non GAP
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Expenditure	0.215***	0.334***	0.345***	0.334***	0.126	0.334***	0.345***	0.126
	(0.061)	(0.015)	(0.084)	(0.015)	(0.085)	(0.015)	(0.084)	(0.085)
Planted area	0.166***	0.019**	0.174***	0.019**	0.134***	0.019**	0.174***	0.134***
	(0.031)	(0.007)	(0.041)	(0.007)	(0.044)	(0.007)	(0.041)	(0.044)
Irrigation	2.361***	1.675***	2.868***	1.675***	2.055***	1.675***	2.868***	2.055***
	(0.274)	(0.046)	(0.543)	(0.046)	(0.320)	(0.046)	(0.543)	(0.320)
Gender	-0.345	0.091	-1.137**	0.091	-0.064	0.091	-1.137**	-0.064
	(0.291)	(0.049)	(0.449)	(0.049)	(0.356)	(0.049)	(0.449)	(0.356)
Hhld size	0.168**	0.000	0.055	0.000	0.252***	0.000	0.055	0.252***
	(0.075)	(0.014)	(0.117)	(0.014)	(0.092)	(0.014)	(0.117)	(0.092)
Education	-0.158	0.047***	-0.150	0.047***	-0.069	0.047***	-0.150	-0.069
	(0.094)	(0.017)	(0.172)	(0.017)	(0.110)	(0.017)	(0.172)	(0.110)
Member farming	-0.179	-0.088***	-0.190	-0.088***	-0.220	-0.088***	-0.190	-0.220
	(0.100)	(0.020)	(0.178)	(0.020)	(0.117)	(0.020)	(0.178)	(0.117)
Distance	-0.020	-0.020**	-0.056*	-0.020**	0.046	-0.020**	-0.056	0.046
	(0.026)	(0.009)	(0.032)	(0.009)	(0.053)	(0.009)	(0.032)	(0.053)
Transport	-0.387	-0.181***	-0.146	-0.181***	-0.263	-0.181***	-0.146	-0.263
	(0.244)	(0.044)	(0.476)	(0.044)	(0.283)	(0.044)	(0.476)	(0.283)
Rice	1.566	1.533***	2.934	1.533***	0.963	1.533***	2.934	0.963
	(0.919)	(0.111)	(1.669)	(0.111)	(1.073)	(0.111)	(1.669)	(1.073)
Cassava	1.029	0.938***	1.707	0.938***	0.318	0.938***	1.707	0.318
	(1.070)	(0.147)	(2.238)	(0.147)	(1.218)	(0.147)	(2.238)	(1.218)
(Intercept)	0.788	0.901***	0.832	0.901***	0.621	0.901***	0.832	0.621
	(0.981)	(0.130)	(1.859)	(0.130)	(1.144)	(0.130)	(1.859)	(1.144)
n	380	9610	120	9610	260	9610	120	260
Adjusted R^2	0.430	0.275	0.673	0.275	0.293	0.275	0.673	0.293
F-statistic	$26.95^{***}_{11,368}$	$332.70^{***}_{11,9598}$	$23.31^{***}_{11,108}$	$332.70^{***}_{11,9598}$	$10.77^{***}_{11,248}$	$332.70^{***}_{11,9598}$	$23.31^{***}_{11,108}$	$10.77^{***}_{11,248}$
Causal inference								
Predicted mean	3.647	3.321	4.392	3.321	3.298	3.321	4.392	3.298
(SE)	(0.096)	(0.013)	(0.246)	(0.013)	(0.089)	(0.013)	(0.246)	(0.089)
ATE	**0.326*** **		**1.071*** **		**-0.023**		**1.094*** **	

** p < 0.05, *** p < 0.01

Table 3.5 Robustness: ESR outcome regression estimating REY

Explanatory variable	Full sample (n1)		ACs with GAP (n2)		ACs without GAP (n3)		Adopters vs non-adopters (n4)	
	Members	Non-members	Mem GAP	Non-members	Mem non GAP	Non-members	Gap adopters	Non-adopters
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Expenditure	0.230***	0.334***	0.315***	0.334***	0.173**	0.334***	0.315***	0.173**
	(0.059)	(0.015)	(0.081)	(0.015)	(0.085)	(0.015)	(0.081)	(0.085)
Planted area	0.173***	0.018**	0.205***	0.018**	0.139***	0.018**	0.205***	0.139***
	(0.031)	(0.007)	(0.047)	(0.007)	(0.043)	(0.007)	(0.047)	(0.043)
Irrigation	2.183***	1.644***	2.650***	1.644***	1.912***	1.644***	2.650***	1.912***
	(0.283)	(0.046)	(0.566)	(0.046)	(0.337)	(0.046)	(0.566)	(0.337)
Gender	-0.367	0.052	-0.924*	0.052	-0.243	0.052	-0.924	-0.243
	(0.307)	(0.049)	(0.480)	(0.049)	(0.382)	(0.049)	(0.480)	(0.382)
Hhld size	0.160*	-0.039**	0.043	-0.039**	0.197*	-0.039**	0.043	0.197
	(0.083)	(0.015)	(0.137)	(0.015)	(0.103)	(0.015)	(0.137)	(0.103)
Education	-0.113	0.043**	-0.085	0.043**	-0.028	0.043**	-0.085	-0.028
	(0.092)	(0.017)	(0.173)	(0.017)	(0.111)	(0.017)	(0.173)	(0.111)
Member farming	-0.159	-0.089***	-0.158	-0.089***	-0.158	-0.089***	-0.158	-0.158
	(0.101)	(0.020)	(0.189)	(0.020)	(0.119)	(0.020)	(0.189)	(0.119)
Distance	0.002	-0.062***	-0.046	-0.062***	0.042	-0.062***	-0.046	0.042
	(0.036)	(0.011)	(0.056)	(0.011)	(0.065)	(0.011)	(0.056)	(0.065)
Transport	-0.197	-0.416***	0.120	-0.416***	-0.306	-0.416***	0.120	-0.306
	(0.322)	(0.058)	(0.662)	(0.058)	(0.374)	(0.058)	(0.662)	(0.374)
Rice	1.578	1.525***	2.751	1.525***	1.139	1.525***	2.751	1.139
	(0.991)	(0.111)	(2.206)	(0.111)	(1.130)	(0.111)	(2.206)	(1.130)
Cassava	0.894	0.950***	1.030	0.950***	0.612	0.950***	1.030	0.612
	(1.120)	(0.147)	(2.640)	(0.147)	(1.256)	(0.147)	(2.640)	(1.256)
MillsRatioAdt1	0.775		0.305		0.340		0.305	0.340
	(0.831)		(1.464)		(1.034)		(1.464)	(1.034)
MillsRatioAdt0		4.910***		4.910***		4.910***		
		(0.805)		(0.805)		(0.805)		
(Intercept)	-1.041	0.901***	-0.052	0.901***	-0.097	0.901***	-0.052	-0.097
	(2.386)	(0.130)	(3.855)	(0.130)	(3.035)	(0.130)	(3.855)	(3.035)
n	378	9580	120	9580	258	9580	120	258
Adjusted R^2	0.414	0.278	0.626	0.278	0.289	0.278	0.626	0.289
Log.Likelihood	-821.112	-20171.841	-243.121	-20171.841	-560.245	-20171.841	-243.121	-560.245
F-statistic	$23.18^{***}_{12,365}$	$308.90^{***}_{12,9567}$	$17.59^{***}_{12,107}$	$308.90^{***}_{12,9567}$	$9.72^{***}_{12,245}$	$308.90^{***}_{12,9567}$	$17.59^{***}_{12,107}$	$9.72^{***}_{12,245}$
Causal inference								
Predicted mean (SE)	3.701 (0.096)	3.325 (0.013)	4.410 (0.236)	3.325 (0.013)	3.371 (0.091)	3.325 (0.013)	4.410 (0.236)	3.371 (0.091)
ATE	**0.376*****		**1.085*****		**0.046**		**1.038*****	

** p < 0.05, *** p < 0.01

3.4 Heterogeneous impact of AC membership on farm profit

Table 3.6 presents the estimates of farm profit estimated by the IPWRA, while Table 3.7 shows the robustness checks estimated by the ESR. The statistics show that the model performs well. We found similar estimates for farm profit estimated by IPWRA and ESR, indicating that the findings are plausible. The pattern of heterogeneity of the impact on farm profit is similar to that on REY. Without CamGAP, the estimate using a broad treatment, which accounts for only the AC membership, statistically significantly improved farm profit by 0.35 million riels per year. This makes the result consistent with previous empirical evidence (e.g., Hoken & Su, 2018; Tran et al., 2022; Wu et al., 2023). We extended the analysis to consider CamGAP, and we found that AC membership positively impacted farm outcomes only in the case where CamGAP was involved. AC members who adopted CamGAP attained 1.08 million riels per year higher than non-members. By contrast, there was no statistically significant difference in farm profit between AC members who did not adopt CamGAP and non-members. AC members who adopted CamGAP received 1.08 million riels in farm profit per year, higher than non-adopters.

Table 3.6 IPWRA outcome regression estimating farm profit

Explanatory variable	**Full sample (n1)**		**ACs with GAP (n2)**		**ACs without GAP (n3)**		**Adopters vs non-adopters (n4)**	
	Members	**Non-members**	**Mem GAP**	**Non-members**	**Mem non GAP**	**Non-members**	**Gap adopters**	**Non-adopters**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Expenditure	-0.732***	-0.552***	-0.603***	-0.552***	-0.847***	-0.552***	-0.603***	-0.847***
	(0.084)	(0.018)	(0.125)	(0.018)	(0.112)	(0.018)	(0.125)	(0.112)
Planted area	0.200***	0.072***	0.139**	0.072***	0.213***	0.072***	0.139**	0.213***
	(0.042)	(0.009)	(0.061)	(0.009)	(0.058)	(0.009)	(0.061)	(0.058)
Irrigation	1.659***	1.676***	2.906***	1.676***	1.031**	1.676***	2.906***	1.031**
	(0.374)	(0.056)	(0.808)	(0.056)	(0.423)	(0.056)	(0.808)	(0.423)
Gender	0.188	0.208***	-0.721	0.208***	0.378	0.208***	-0.721	0.378
	(0.398)	(0.060)	(0.668)	(0.060)	(0.471)	(0.060)	(0.668)	(0.471)
Hhld size	0.273***	-0.011	-0.217	-0.011	0.540***	-0.011	-0.217	0.540***
	(0.103)	(0.017)	(0.174)	(0.017)	(0.122)	(0.017)	(0.174)	(0.122)
Education	0.044	0.040	0.175	0.040	0.044	0.040	0.175	0.044
	(0.128)	(0.021)	(0.255)	(0.021)	(0.145)	(0.021)	(0.255)	(0.145)
Member farming	-0.355***	-0.041	-0.116	-0.041	-0.516***	-0.041	-0.116	-0.516***
	(0.136)	(0.025)	(0.264)	(0.025)	(0.154)	(0.025)	(0.264)	(0.154)
Distance	0.022	-0.010	0.001	-0.010	0.060	-0.010	0.001	0.060
	(0.036)	(0.011)	(0.048)	(0.011)	(0.071)	(0.011)	(0.048)	(0.071)
Transport	0.323	0.334***	0.745	0.334***	0.406	0.334***	0.745	0.406
	(0.333)	(0.054)	(0.709)	(0.054)	(0.374)	(0.054)	(0.709)	(0.374)
Rice	-0.099	-1.658***	-1.136	-1.658***	0.241	-1.658***	-1.136	0.241
	(1.255)	(0.137)	(2.482)	(0.137)	(1.419)	(0.137)	(2.482)	(1.419)
Cassava	0.098	-0.340	-1.509	-0.340	0.309	-0.340*	-1.509	0.309
	(1.462)	(0.181)	(3.329)	(0.181)	(1.610)	(0.181)	(3.329)	(1.610)
(Intercept)	2.034	3.491***	5.471*	3.491***	0.647	3.491***	5.471	0.647
	(1.340)	(0.160)	(2.765)	(0.160)	(1.512)	(0.160)	(2.765)	(1.512)
n	380	9610	120	9610	260	9610	120	260
Adjusted R^2	0.182	0.157	0.210	0.157	0.241	0.157	0.210	0.241
F-statistic	$8.67^{***}_{11,368}$	$164.00^{***}_{11,9598}$	$3.88^{***}_{11,108}$	$164.00^{***}_{11,9598}$	$8.48^{***}_{11,248}$	$164.00^{***}_{11,9598}$	$3.88^{***}_{11,108}$	$3.48^{***}_{11,93}$
Causal inference								
Predicted mean (SE)	2.210 (0.078)	1.859 (0.011)	2.938 (0.157)	1.859 (0.011)	1.864 (0.108)	1.859 (0.011)	2.938 (0.157)	1.428 (0.154)
ATE	**0.352*** **		**1.080*** **		**0.005**		**1.075*** **	

** p < 0.05, *** p < 0.01

Table 3.7 Robustness checks: ESR outcome regression estimating farm profit

Explanatory variable	Full sample (n1)		ACs with GAP (n2)		ACs without GAP (n3)		Adopters vs non-adopters (n4)	
	Members	Non-members	Mem GAP	Non-members	Mem non GAP	Non-members	Gap adopters	Non-adopters
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Expenditure	-0.751***	-0.553***	-0.690***	-0.553***	-0.834***	-0.553***	-0.690***	-0.834***
	(0.080)	(0.018)	(0.109)	(0.018)	(0.112)	(0.018)	(0.109)	(0.112)
Planted area	0.237***	0.073***	0.206***	0.073***	0.233***	0.073***	0.206***	0.233***
	(0.042)	(0.009)	(0.063)	(0.009)	(0.057)	(0.009)	(0.063)	(0.057)
Irrigation	1.251***	1.565***	2.530***	1.565***	0.657	1.565***	2.530***	0.657
	(0.380)	(0.056)	(0.761)	(0.056)	(0.446)	(0.056)	(0.761)	(0.446)
Gender	-0.281	0.074	-1.359**	0.074	-0.034	0.074	-1.359**	-0.034
	(0.411)	(0.060)	(0.644)	(0.060)	(0.506)	(0.060)	(0.644)	(0.506)
Hhld size	0.097	-0.147***	-0.427**	-0.147***	0.322**	-0.147***	-0.427**	0.322**
	(0.111)	(0.018)	(0.184)	(0.018)	(0.136)	(0.018)	(0.184)	(0.136)
Education	0.156	0.026	0.061	0.026	0.202	0.026	0.061	0.202
	(0.124)	(0.021)	(0.232)	(0.021)	(0.147)	(0.021)	(0.232)	(0.147)
Member farming	-0.404***	-0.042	-0.074	-0.042	-0.504***	-0.042	-0.074	-0.504***
	(0.136)	(0.024)	(0.254)	(0.024)	(0.158)	(0.024)	(0.254)	(0.158)
Distance	-0.124**	-0.159***	-0.269***	-0.159***	-0.072	-0.159***	-0.269***	-0.072
	(0.048)	(0.014)	(0.075)	(0.014)	(0.085)	(0.014)	(0.075)	(0.085)
Transport	-0.404	-0.487***	-1.231	-0.487***	-0.027	-0.487***	-1.231	-0.027
	(0.432)	(0.070)	(0.889)	(0.070)	(0.495)	(0.070)	(0.889)	(0.495)
Rice	0.509	-1.712***	2.548	-1.712***	0.515	-1.712***	2.548	0.515
	(1.328)	(0.135)	(2.965)	(0.135)	(1.494)	(0.135)	(2.965)	(1.494)
Cassava	0.637	-0.299	2.530	-0.299	0.511	-0.299	2.530	0.511
	(1.501)	(0.179)	(3.548)	(0.179)	(1.660)	(0.179)	(3.548)	(1.660)
MillsRatioAdt1	-2.963***		-6.996***		-1.936		-6.996***	-1.936
	(1.113)		(1.967)		(1.367)		(1.967)	(1.367)
MillsRatioAdt0		17.107***		17.107***		17.107***		
		(0.976)		(0.976)		(0.976)		
(Intercept)	9.812***	3.500***	20.090***	3.500***	6.275	3.500***	20.090***	6.275
	(3.197)	(0.158)	(5.180)	(0.158)	(4.013)	(0.158)	(5.180)	(4.013)
n	378	9580	120	9580	258	9580	120	258
Adjusted R^2	0.227	0.183	0.354	0.183	0.235	0.183	0.354	0.235
Log.Likelihood	-931.668	-22014.391	-278.570	-22014.391	-632.346	-22014.391	-278.570	-632.346
F-statistic	$10.22^{***}_{12,365}$	$180.10^{***}_{12,9567}$	$6.43^{***}_{12,107}$	$180.10^{***}_{12,9567}$	$7.57^{***}_{12,245}$	$180.10^{***}_{12,9567}$	$6.43^{***}_{12,107}$	$7.57^{***}_{12,245}$
Causal inference								
Predicted mean (SE)	2.247 (0.085)	1.860 (0.012)	2.768 (0.192)	1.860 (0.012)	2.005 (0.107)	1.860 (0.012)	2.768 (0.192)	2.005 (0.107)
ATE	**0.387***		**0.908***		**0.145**		**1.038***	

** p < 0.05, *** p < 0.01

4. Conclusions, limitations and implications

This study aims to examine the heterogeneous impact of AC membership on farm yield and farm profit. We used the most recent country-wide data that allows the study to account for all crops grown by farmers' households. Because rice remained the major crop in Cambodia, we computed REY to measure comparable yields from different crops. The data also allows the study to compute meaningful farm profit by accounting for key inputs, including fertilisers, pesticides, seeds, opportunity cost of labour and opportunity cost of using own seed for planting. We distinguished AC members into two distinct groups under the condition of CamGAP adoption status to yield accurate insights into the impact of AC membership on REY and farm profit. Empirically, we used IPWRA to estimate the heterogeneity of impact, while ESR was employed for the robustness checks. We found consistent results between the two methods, indicating the plausible findings of the important role of CamGAP in catalysing the significant and positive impact of AC membership on the farm outcomes in Cambodia. Because only 46% of sampled AC members adopted CamGAP, the findings suggest that policymakers should put more effort into promoting CamGAP in ACs.

In short, it can be concluded that ACs adopting GAP statistically and significantly improve farm outcomes in Cambodia. Those that did not adopt GAP have no impact on farm outcomes. ACs that have not adopted CamGAP (54% of the sampled ACs) should improve the structures of transactional relationships (vertical coordination or integration) with downstream actors, e.g., supermarkets, processors, retailers, exporters, etc, to get better access to technical trainings to comply with CamGAP certification to improve farm productivity and profit. The public-private and producer partnership (4Ps) could be a potential mechanism to fill the gap, and further studies should shed light on this area to contribute to sustainable agricultural and inclusive growth in Cambodia.

Due to data constraints, this study excluded expenditures on post-harvest facilities and standard certification incurred by AC members. This leaves a question of whether AC membership has a positive relationship with farm outcomes after accounting for such additional costs beyond production activities, which should be answered by future studies.

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