Impact of agricultural cooperative membership on Cambodian rice yield and gross margin

Narith Roeun, PhD student, Lincoln University, New Zealand
Email: narith.roeun@lincolnuni.ac.nz;
roeun.narith@gmail.com

Abstract

The potential benefits of agricultural cooperatives for small-scale farmers have been well-documented in the literature, and there is a growing body of evidence from developing countries showing that these benefits can be realised. Cambodia introduced new cooperative legislation in 2013 and has provided policy and material support for the establishment of 'modern' cooperatives over the past ten years. However, it is estimated that only 7% of the country's small-scale farmers are members of registered agricultural marketing cooperatives (ACs). As a starting point to explain this low uptake by farmers, this study investigates the impact of AC membership on rice yield and gross margin in Cambodia using nationally representative data from the Cambodia Agricultural Survey, 2021. Rice is Cambodia's principal crop and food staple. Of the 11,130 rice farmers identified in the national sample, 9,855 had similar cropping systems and were selected for analysis using PSM and 2SLS methods to assess impact. Endogenous switching regression (ESR) was also applied to check the robustness of the results. AC membership was estimated to increase rice yield by 0.49 tons per hectare, and gross margin by 110.21 thousand riels per ton. Taken together and expressed in US dollars, the combined effect of better yields and prices adds approximately US$146 to a non-member's farm gross margin, an increase of 73%. In this study, gross margin represents the return to land and management as the opportunity costs of own labour and rice seed were accounted for. The estimated financial impact of AC membership represents a meaningful gain to small-scale rice farmers in Cambodia, and lends support to policy interventions aimed at promoting the cooperative movement. However, this finding begs the question of why so few farmers participate in ACs when the benefits are not trivial. Has the pace of policy implementation been too slow? Do farmers lack credible information about the benefits of modern cooperatives, or is the problem some mix of these supply and demand-side forces? Further research is required to answer these questions and to offer well-informed policy recommendations.

Keywords: Agricultural cooperatives, rice yield, gross margin, Two-stage least squares, Endogenous Switching Regression

1 INTRODUCTION

In many countries, farmers are encouraged to participate in agricultural cooperatives (ACs) because these organisations are believed to function as collective entities empowering farmers to overcome common obstacles in farm production and marketing (Iliopoulos, 2013; Kumar, Saroj, Joshi, & Takeshima, 2018; Liu, Ma, Renwick, & Fu, 2019; Sebhatu et al., 2021). First, ACs facilitate farmers' access to various resources and services, including credit (Jiang, Li, & Mi, 2024; Ma, Abdulai, & Goetz, 2018; Peng, Wang, & Zhou, 2022), new agricultural technologies (Abebaw & Haile, 2013; Chagwiza, Muradian, & Ruben, 2016; Ma, Abdulai, & Goetz, 2018; Manda et al., 2020), agricultural training and productive agricultural inputs such as fertilisers and seeds (Abate, Francesconi, & Getnet, 2014; Abebaw & Haile, 2013; Verhofstadt & Maertens, 2014). Such improvement can enable farmers to obtain better farm productivity, which is the crucial outcome agricultural policies aim to achieve (Abdul-Rahaman & Abdulai, 2018; Ariyaratne, Featherstone, & Langemeier, 2006;

Kumar et al., 2018; Lin, Wang, Jin, Yang, & Li, 2022; Ma & Abdulai, 2016; Ma, Renwick, Yuan, & Ratna, 2018; Ma, Zheng, & Yuan, 2022; Michalek, Ciaian, & Pokrivcak, 2018; Verhofstadt & Maertens, 2014; Wassie, Kusakari, & Masahiro, 2019). Second, ACs play a pivotal role in enhancing market access by leveraging economies of scale and negotiating fair prices for farm outputs (Glover, 1987; Liu, Ma, Renwick, & Fu, 2018; Sivramkrishna & Jyotishi, 2008). The established business structure provided by ACs can provide farmers with lower transaction costs (Barrett et al., 2012; Iliopoulos, 2013; Kelly, Adesina, & Gordon, 2003; Markelova, Meinzen-Dick, Hellin, & Dohrn, 2009; Nilsson, 2001; Poulton, Dorward, & Kydd, 2010). AC members can also access lower input prices through bulk discounts (Gezahegn, Van Passel, Berhanu, D'Haese, & Maertens, 2019). This can lead to an increase in farm income (Wassie et al., 2019) in addition to the attainment of an expected higher yield. In this sense, participation in ACs would be more promising for farmers to improve their livelihoods, especially those in developing countries (Abdul-Rahaman & Abdulai, 2018; Bachke, 2019; Fischer & Qaim, 2012; Gezahegn et al., 2019; Kumar et al., 2018; Vandeplas, Minten, & Swinnen, 2013; Wollni & Zeller, 2007).

A growing body of research highlights the positive impacts of ACs on crop production and marketing performance. Ma and Abdulai (2016, 2017, 2019) found that AC membership significantly enhances apple yields, farm net returns, and household income, while improving Integrated Pest Management (IPM) adoption, respectively. Hao et al. (2018) demonstrated that AC membership influences farmers' sales channels, promoting better food quality and safety. Fischer and Qaim (2012) reported that ACs boost income and innovation in banana farming in Kenya, though with modest price benefits. Ma et al. (2022) showed that ACs reduce yield variance and downside risk in banana farming in China. In the coffee sector, Sivramkrishna and Jyotishi (2008) found that ACs counter monopsony power in Costa Rica, while Mojo, Fischer, and Degefa (2017) and Ortega et al. (2019) highlighted improvements in household income and productivity in Ethiopia and Rwanda, respectively. Additionally, Ito, Bao, and Su (2012) found that ACs significantly enhance the economic status of watermelon farming in China, and Hoken and Su (2018) and Lin et al. (2022) reported substantial benefits for rice farmers in China, with Abdul-Rahaman and Abdulai (2018) noting similar gains for rice farmers in Ghana.

Understanding the impact of AC membership on crops in high global demand, particularly rice, is crucial. Rice is a staple for over 50% of the world's population (USDA, 2024) and is central to the livelihoods of about one-fifth of the global population, with approximately 400 million involved in rural small-scale rice farming (Mishra et al., 2022; The United Nations, 2017). Despite its significance, there is a lack of rigorous studies on how AC membership affects rice farming outcomes in emerging economies that heavily rely on this sector. This study aims to address this gap by examining the impact of AC membership on rice productivity and gross margin in Cambodia, a notable emerging rice producer and exporter with a strong presence in small-scale rice farming. The study provides unbiased estimates, offering valuable insights for policymakers and development practitioners seeking to support and scale AC initiatives in similar contexts.

Recent literature has used different cross-section data methods to assess AC membership's impacts on farm outcomes. The propensity score matching (PSM) method accounts for observed covariates to produce a single dimensional propensity score (p-score) for the average treatment effects on the treated (ATT), addressing the "curse of dimension" problem (Verhofstadt & Maertens, 2015). Another method is inverse probability weighting (IPW). IPW technique relies heavily on the PSM approach, but this method provides better estimates for ATT due to its use of a single-dimensional p-score as a weight, allowing the use of the entire sample rather than sub-setting the treatment group and the controlled group based on p-score matching in the PSM (Blekking, Gatti, Waldman, Evans, & Baylis, 2021; Ma et al., 2022). However, both techniques have been criticised because they can only address selection bias attributed to observed factors; in short, both methods are unable to deal with selection bias originating from unobserved factors. Despite the critiques, the methods have been employed by relevant studies (Abebaw & Haile, 2013; Blekking et al., 2021; Chagwiza et al., 2016; Fischer & Qaim, 2012; Hoken & Su, 2018; Ito et al., 2012; Ortega et al., 2019; Peng et al., 2022; Verhofstadt & Maertens, 2015).

In impact assessment, the other two methods for cross-section data approach encompassing endogenous switching regression (ESR) and two-stage least squared (2SLS) can deal with entire endogeneity problems. In the ESR approach, bias is captured by the inverse Mills ratio (IMR) included in treatment regressions estimated simultaneously for observed participants and non-participants (Hao et al., 2018; Jiang et al., 2024; Kumar et al., 2018; Liu et al., 2019; Ma & Abdulai, 2016, 2017, 2019; Ma et al., 2022; Mojo et al., 2017; Sebhatu et al., 2021). One critique against the ESR to be considered is the difficulty in interpreting causal effects. The ESR relies on predicted values from simultaneous regression, accounting for all effects from covariates for the computation of average treatment effects (ATE) and treatment effects on the treated (ATT). Because of this, the ATE and ATT results are hard to translate into the impact of AC membership. In this sense, the ATE and ATT drawn from the unbiased ESR method seem to be the simple comparison of performance between members and non-members, not specifically the impact of the membership. Unlike the ESR method, the 2SLS method captures the impact of the AC membership or any specific intervention by using the unbiased coefficients in outcome regressions or the second stage. This allows researchers to distinguish between the membership or any particular intervention impact and other covariates (e.g., time-invariant household and farm characteristics) when only cross-section data is available. Given the promising advantages, this study employs the 2SLS method by proposing a new valid instrument variable for AC membership, which will be described in the following sections. This study uses the ESR for robustness checks.

This paper is presented using the following structures. Section 2 outlines the background of the research on rice production and ACs in Cambodia. Section 3 describes the data and empirical methods utilised in the analysis. Second 4 provides empirical findings and discussion, and section 5 concludes the study with policy implications.

2 RESEARCH BACKGROUND

2.1 Cambodia’s rice export and production

Cambodia, a prominent rice producer and exporter in Southeast Asia, has significantly transformed its rice sector over the past decade. After emerging in the global rice value chain in 2010, Cambodia's rice exports surged dramatically from USD 34.745 million in 2010 to a peak of USD 470.67 million in 2020, according to ITC Trade Map (2024). Despite a subsequent decline in exports in the following years, the country's rice production has continued to grow. In 2022, Cambodia harvested 11.62 million tons of rice from 3.3 million hectares, as reported by FAOSTAT (2024). This growth in production is reflected in an increasing trend in rice yields, positioning Cambodia favourably among other major rice-producing countries. The expanding rice sector underscores its vital role in Cambodia's economic development, providing not only a staple food for its population but also contributing significantly to trade and economic growth.

2.2 AC development in Cambodia

Along with the diversification of the agricultural sector from food security to commercialisation and export-oriented, ACs have become a pivotal instrument for Cambodia in order to achieve its objectives. Three years after the rice export policy was in force, a law on ACs was promulgated in 2013. Rice exports have sharply increased, and more ACs have been registered across the country. Chhinh, Sok, Sou, Nguonphan, and Pheakdey (2022) collected data from the Ministry of Agriculture, Forestry and Fisheries (MAFF) and reported the increasing number of registered ACs from 2018 to

1200 between 2010 and 2020, respectively. From the same information source, there were 144,306 members (53,703 females), implying that, on average, there were 120 members per registered AC in 2020. Registered ACs receive resources to strengthen their financial management, marketing management, post-harvest facilities, and management skills (Chhinh et al., 2022). The government also established Cambodia's Agriculture and Rural Development Bank (ARDB), which offers ACs low-interest loans (MAFF, 2022). In its latest agricultural development policy, MAFF (2022) emphasised the need to strengthen AC performance by providing favourable electricity tariffs, increasing the adoption of Good Agricultural Practice (GAP), and promoting ACs in public-private-producer partnerships (4Ps). A recent study found that 76% of ACs have sale agreements with their clients (Ngo & Khon, 2023). Viewed against this background of substantial policy support for AC development over the past decade, it is reasonable to hypothesise that AC membership has improved the productivity and income of Cambodia's small-scale rice farmers, but the advantages of the membership have not been well known by most Cambodian farmers because almost a decade after the release of the law on ACs and development efforts, only 7% of Cambodian farmers have held an AC membership.

3 ESTIMATION STRATEGIES

3.1 Data

This study uses a nationally representative dataset called Cambodia Agricultural Survey 2021 (CAS2021), which was released in February 2024 by the National Institute of Statistics (NIS) of the Ministry of Planning, Cambodia. CAS2021, conducted between November and December 2021 by the NIS and the Ministry of Agriculture, Forestry and Fisheries with FAO support, was a part of the "50x2030 Initiative" funded by the World Bank, FAO, and IFAD to enhance national agricultural data systems. After a critical data examination, we found that the data fit the purpose of this study, and we are confident we can proceed with the analysis. The data is promising for the topic because it contains important variables of interest, with a total sample of 11,130 rice-producing households. To ensure accuracy, this study selected 9,855 households that had similar cropping systems.

3.2 Model to assess the impact of AC membership

This study aims to provide unbiased estimates and meaningful interpretation of the causal effects of AC membership rather than merely comparing outcomes between members and non-members. To achieve this, we adopted the 2SLS method. Given the large and imbalanced data, we also used the PSM method with nearest neighbour matching (caliper of 0.2 and matching ratio of 1:10) to match members and non-members with similar characteristics for inclusion in the 2SLS outcome models and causal effect investigation using the Average Treatment Effect (ATE) and Average Treatment Effect on the Treated (ATT). Monte Carlo simulations indicate that a caliper width of 0.2 of the combined standard deviation of the probit predicted probability improves accuracy in estimating treatment effects (Wang et al., 2013). We chose a matching ratio 1:10 to retain valuable data and minimise the risk of missing values. The matching was performed using the R MatchIt package algorithm (Ho, Imai, King, & Stuart, 2011). The probit model is written as

$$P = \beta_0 + \beta_1 X_{1a} + \beta_2 X_{2a} + \beta_3 X_{3a} + \cdots + \beta_k X_{ka} + e_1 \quad (1)$$

where, P is the probability of AC membership; β_0 is a constant of the probit model; β_1 to β_k are coefficients of explanatory variables X_{1a} to X_{ka}; e_1 is the error term of the probit model (1). We denote the predicted probability as $\hat{P}_{1a}$ which is used for the p-score generation using a cut-point of 0.5 from a normal distribution of N [0,1], denoted as $\hat{P}_{1a}$, where $\hat{P}_{1a} \geq 0.5$ refers to predicted AC members, otherwise predicted non-members. However, to improve the prediction, this study uses the p-score from a normal distribution of $N\hat{P}_{1b}$ [E ($\hat{P}_{1a}$),SD ($\hat{P}_{1a}$)] instead of N [0,1], denoted as $\hat{P}_{1b}$, where $\hat{P}_{1b} \geq 0.5$ refers to predicted AC members, otherwise predicted non-members.

Based on the procedure, we generate two subsets of matched cases from the original sample (n). The first subset (n_1) comprises all matched cases, while the second subset (n_2) includes only cases predicted to be AC members ($\hat{P}_{1b} \geq 0.5$). Given Equation (1) serves for creating these two subsets, we regress another Probit model with an instrumental variable (IV) included serving as the first stage of the 2SLS, written as

$$P = \alpha_0 + \alpha_1 X_{1a} + \alpha_2 X_{2a} + \alpha_3 X_{3a} + \cdots + \alpha_k X_{ka} + \alpha_{kiv} IV + e_2 \quad (2)$$

where, P is the probability of AC membership; α_0 is a constant of Equation (4); α_1 to α_k are coefficients of explanatory variables X_{1a} to X_{ka}; α_{kiv} is a coefficient of the instrumental variable IV; e_2 is the error term of Equation (2). Equation (2) also suffers from imbalanced data, causing weak classification into AC members given the dominant numbers of non-members in the original dataset n. This means that the predicted AC membership, hereafter denoted as $\hat{P}_{2a}$ estimated by Equation (2) cannot be regressed by the outcome regression given the weak prediction. We adopted the normal distribution of the predicted probability of $N\hat{P}_{2b}$[E ($\hat{P}_{2a}$),SD ($\hat{P}_{2a}$)] to improve the predicted probability, denoted as $\hat{P}_{2b}$, where $\hat{P}_{2b} \geq 0.5$ refers to cases predicted to be AC members. We used the improved predicted AC membership $\hat{P}_{2b}$ instead of $\hat{P}_{2a}$ in the outcome regression, which is written as

$$Y = \theta_0 + \theta_1 X_{1b} + \theta_2 X_{2b} + \theta_3 X_{3b} + \cdots + \theta_k X_{kb} + \theta_{kp} \hat{P}_{2b} + e_3 \quad (3)$$

where, Y is the outcome (dependant) variable of interest; θ_0 is the constant of Equation (3); θ_1 to θ_k are coefficients of explanatory variables X_{1b} to X_{kb}; θ_{kp} is the coefficient of the probability of AC membership (P); e_3 is the error term of Equation (3). Equation (3) eliminates endogeneity, which is commonly encountered by ordinary least squares (OLS) through the use of $\hat{P}_{2b}$ instead of P, which is endogenous. At the same time, Equation (3) resolves bias from imbalanced data through the use of $\hat{P}_{2b}$ instead of $\hat{P}_{1b}$. We regress Equation (3) using subsets n_1 and n_2 to estimate the ATE and ATT, respectively. We adjusted the standard errors using the approach detailed by (Gujarati, 2003, p. 791).

The ATE measures the impact of offering Agricultural Cooperative (AC) membership to all farmers, while the ATT measures the impact on those who actually join. ATE is crucial for policymakers as it indicates the overall effect of AC membership on the entire farming population. This helps broadly evaluate the potential benefits of promoting AC membership. ATT, however, is relevant to farmers deciding whether to join, as it shows the impact on those who participate. This study focuses on ATE estimates to determine the overall impact of AC membership on rice yield and gross margin, providing insights for policy decisions affecting the general farmer population given the current low observed AC membership rate.

The reliability of the 2SLS estimates hinges on the validity of its IV (Heckman, Ichimura, & Todd, 1998; Ravallion, 2007). IVs must be strongly correlated with P (i.e., Corr [IV, P] ≠ 0) but uncorrelated with the residual term in Equation (3) (i.e., Corr [IV, e_3] = 0). We use the number of crops grown by farmers' households as an IV, assuming that farmers with a wider variety of crops have different needs and benefits from joining an AC compared to those with fewer crops. Cooperatives offer better seeds, fertilisers, shared knowledge, and marketing resources that benefit diversified farming operations. Therefore, the number of crops a farmer grows can influence their likelihood of joining an AC. This variable should affect productivity and revenue only through AC membership, as the benefits provided by the ACs directly enhance these outcomes.

4 RESULTS AND DISCUSSION
4.1 Descriptive statistics

Table 1 summarises the variables used in the study, including definitions, sample sizes, means, and standard errors. Only 3% of households are members of an AC, highlighting the low membership rate in Cambodia's rice ACs. The average paddy yield is 2.56 tons per hectare, lower than the FAOSTAT (2024) reported yield of 3.35 tons per hectare. The mean gross margin is 249.22 thousand riels per ton. The average paddy farm-gate price is 0.89 riels per kilogram, and the average expenditure on inputs is 1,438.06 thousand riels per hectare, equivalent to USD 359.52. This input expenditure is higher than the wet season expenditure of USD 298 but lower than the dry season expenditure of USD 856 per hectare as CDRI (2012) reported. The mean fertiliser price is 2.68 thousand riels per kilogram, which is lower than the range of 3.20 to 4.80 thousand riels per kilogram reported by Vuthy (2020).

Table 1: Variable definitions and summary statistics

Variable	Definition	n	Mean	SE
Treated variable				
AC	1=Member of a registered agricultural marketing cooperative, 0 otherwise	9,850	0.03	0.00
Outcome variables				
Yield	Paddy yield per hectare (ton/ha)	9,852	2.56	0.02
Gross margin	Gross margin per ton (riel 10^3/ton)	7,567	249.22	12.49
Explanatory variables				
Price	Paddy farm-gate price per kilogram (riel 10^3/kg)	9,852	0.89	0.00
Expenditure	Expenditure on fertilisers, seeds, and labour used to grow rice (riel 10^3/ha)	7,567	1,438.06	32.34
Hired workers	1=Hired additional labour to grow rice, 0 otherwise	9,855	0.24	0.00
Loans	1=Use loans for agriculture, 0 otherwise	9,781	0.01	0.00
Rice area	Total area planted to rice (ha)	9,855	1.31	0.02
Crops	Number of different crops grown (#)	9,855	1.77	0.01
Soil types	1=Clay or loam soil, 0 otherwise	9,850	0.93	0.00
Farmland	Farmland endowment (ha per adult equivalent[1])	9,845	0.62	0.01
Land title	1=Broad bundle of assured property rights to land, 0 otherwise	9,805	0.08	0.00
Distance	Distance from dwelling to farms (hours)	9,850	0.29	0.00
Hhld size	Number of people in the household (#)	9,850	5.46	0.03
Training	1=If at least one household member has participated in agricultural training, 0 otherwise	9,850	0.11	0.00
Education	Number of household members with at least secondary schooling (#)	9,850	1.49	0.01
Gender	1=Male headed household, 0 otherwise	9,719	0.78	0.00

Farm characteristics show that 93% of sample farms have clay or loam soil, but only 1% use loans for agriculture. The average rice-planted area is 1.31 hectares, with a farmland endowment of 0.62 hectares per adult equivalent. Only 8% of farms have officially registered land titles. On average, farms hire additional labour (24%), and the mean distance from dwelling to farms is 0.29 hours. Household characteristics reveal an average size of 5.46 members, with 11% joining in agricultural training, 1.49 members with at least secondary education, and 78% male-headed households.

[1] Adult equivalent = ((members 18-64 years old) + 0.5(member < 18 and > 64 years old)).

Table 2 highlights that AC members exhibit significantly better agricultural performance compared to non-members, with markedly higher yields and gross margins reflecting enhanced productivity and profitability. This is coupled with greater investment in inputs and increased use of hired labour, which suggests that AC members allocate more resources to their farming activities, resulting in better outcomes. They also benefit from improved access to financial resources, as indicated by their higher loan uptake, and manage larger rice cultivation areas and more farmland. Additionally, AC members have more secure land tenure, access to higher-quality soil, higher educational attainment, and more agricultural training participation. While these factors collectively contribute to their superior performance, the analysis based on mean comparisons may overlook other potential confounding variables.

Table 2: Differences in characteristics of AC members and non-members

Variable	AC members			Non-members			Difference
	n	Mean	SE	n	Mean	SE	
Yield	319	3.39	0.12	9,528	2.54	0.02	0.85***
Gross margin	215	380.21	35.75	7,348	245.38	12.82	134.83***
Price	319	0.88	0.01	9,528	0.89	0.00	- 0.01
Expenditure	215	1,591.50	83.28	7,348	1,433.60	33.22	157.89*
Hired workers	319	0.45	0.03	9,531	0.23	0.00	0.21***
Loans	306	0.03	0.01	9,470	0.01	0.00	0.02*
Rice area	319	1.72	0.11	9,531	1.29	0.02	0.43***
Crops	319	2.24	0.07	9,531	1.76	0.01	0.49***
Farmland	319	0.76	0.05	9,521	0.61	0.01	0.15***
Land title	318	0.12	0.02	9,482	0.08	0.00	0.04**
Soil types	319	0.97	0.01	9,526	0.93	0.00	0.04***
Distance	319	0.28	0.02	9,526	0.30	0.00	- 0.02
Hhld size	319	5.63	0.16	9,526	5.45	0.03	0.17
Training	319	0.68	0.03	9,526	0.09	0.00	0.59***
Education	319	1.92	0.08	9,526	1.47	0.01	0.45***
Gender	316	0.88	0.02	9,398	0.78	0.00	0.10***

*p<0.1; **p<0.05; ***p<0.01

4.2 Determinants of AC membership

Table 5 presents the results of a Probit model analysing factors affecting AC membership. The results indicate that access to clay or loam soil increases the likelihood of AC membership by 10%, highlighting the importance of high-quality soil for decision-making related to AC participation. Secure land tenure is also a significant factor, with land title holders being 6% more likely to join ACs. Additionally, cultivating a greater variety of crops enhances membership probability by 4%, reflecting the advantages of diversified farming. Distance from the farm to the dwelling negatively impacts membership, with each additional hour reducing the likelihood by 5%, likely due to logistical challenges. Male-headed households are 6% more likely to be AC members, suggesting gender-related disparities in access to AC resources. Education has a positive effect, with more educated households being 3% more likely to join ACs. Conversely, larger household sizes slightly reduce the probability of membership by 1%, potentially due to increased internal demands. The model's McFadden's Pseudo R^2 of 0.06 indicates modest explanatory power due to imbalanced treatment that only 3% of farmers are observed as AC members, but the significant Chi-squared test confirms the overall validity of the model. Correct classification is also enhanced by the adjustment of the probability normal distribution, as detailed in Section 3.2.

Table 3: Probit model parameter estimates with IV included

Explanatory variable	Estimate	Marginal Effect	SE	VIF
Soil types	0.42***	0.10	0.15	1.01
Farmland	0.02	0.00	0.03	1.23
Land title	0.22***	0.06	0.08	1.01
Crops	0.16***	0.04	0.02	1.17
Distance	- 0.19**	- 0.05	0.09	1.09
Gender	0.25***	0.06	0.07	1.03
Education	0.12***	0.03	0.02	1.18
Hhld size	- 0.02**	- 0.01	0.01	1.22
Intercept	- 2.81***		0.17	
n	9661			
Log Likelihood	- 1323.40			
AIC	2664.80			
McFadden's Pseudo R^2	0.06			
X^2 (8)	127.20			
P(> X^2)	0000			

*p<0.1; **p<0.05; ***p<0.01

4.3 Impact of AC membership on rice yield and gross margin

Table 4 depicts 2SLS estimates for ATE and ATT for rice yield, while Table 5 presents the estimates for gross margin. The ATE and ATT estimates consistently show the significant impact of AC membership on rice yield, increasing by 0.49 and 0.61 tons per hectare, respectively. Adequate

Table 4: 2SLS(IV) parameter estimates for paddy yield (ton/ha)

Explanatory variable	ATE			ATT		
	Estimate	Adjusted SE	VIF	Estimate	Adjusted SE	VIF
Predicted AC	**0.49*****	0.12	1.06	**0.61*****	0.19	1.03
Soil type	0.21*	0.11	1.02	0.16	0.20	1.01
Rice area	- 0.06***	0.02	1.30	- 0.04*	0.02	1.29
Irrigation	1.08***	0.07	1.04	1.10***	0.09	1.06
Loans	0.52*	0.28	1.02	0.58*	0.34	1.02
Distance	- 0.15	0.10	1.07	- 0.03	0.17	1.07
Gender	0.16**	0.07	1.05	0.28***	0.10	1.03
Hhld size	- 0.03***	0.01	1.03	- 0.04***	0.01	1.03
Training	0.48***	0.09	1.03	0.54***	0.12	1.03
Log of expenditure	0.56***	0.05	1.17	0.54***	0.06	1.17
Hired workers	0.07	0.07	1.07	- 0.06	0.09	1.08
(Intercept)	- 1.78***	0.33		- 1.82***	0.47	
n	2565			1418		
R^2	0.25			0.25		
Adjusted R^2	0.24			0.24		
F-statistic	$76.41^{***}_{11,2553}$			$42.71^{***}_{11,1406}$		

*p<0.1; **p<0.05; ***p<0.01

Estimated paddy yield ATE and ATT are highlighted in boldface.

irrigation and agricultural training also play crucial roles in enhancing yields, with both showing strong positive impacts. Conversely, larger rice areas and household sizes negatively affect yields, likely due to the complexities of managing larger plots and higher internal demands.

The 2SLS estimates in Table 5 reveal AC membership impact on gross margin, which is statistically significant at the 0.05 level for ATE, highlighting the positively substantial impact on the gross margin through AC membership. The ATT estimate is also positive, but not statistically significant. Price has a strong positive effect on gross margin. At the same time, adequate irrigation also boosts gross margins significantly. Increased expenditure significantly reduces gross margins. The impact of loans is mixed, with ATE showing a non-significant reduction and ATT indicating a significant increase. Distance from dwellings to farms has a significant negative effect on gross margins.

Table 5: 2SLS(IV) parameter estimates for gross margin (riel 10^3/ton)

Explanatory variable	ATE			ATT		
	Estimate	Adjusted SE	VIF	Estimate	Adjusted SE	VIF
Predicted AC	**110.21****	56.34	1.07	**111.89**	92.11	1.03
Price	889.95***	83.02	1.04	784.19***	100.76	1.05
Rice area	- 10.87*	6.31	1.31	- 8.84	7.13	1.31
Log of expenditure	- 574.44***	29.69	1.17	- 530.73***	33.96	1.17
Soil type	158.02	148.58	1.02	31.34	87.83	1.01
Irrigation	206.62***	40.21	1.07	137.64***	35.72	1.09
Loans	- 278.66	460.47	1.02	159.61*	84.11	1.02
Distance	- 122.48*	64.00	1.07	- 121.79	90.52	1.08
Gender	32.27	38.18	1.05	32.00	66.63	1.03
Hhld size	- 0.33	6.18	1.03	- 1.42	5.43	1.03
Training	35.27	88.69	1.03	101.82*	58.23	1.03
Hired workers	45.24	39.84	1.07	- 0.17	46.45	1.09
(Intercept)	3167.96***	218.18		3105.47***	310.25	
n	2565			1418		
R^2	0.22			0.32		
Adjusted R^2	0.22			0.32		
F-statistic	$61.37^{***}_{12,2552}$			$55.38^{***}_{12,1405}$		

p<0.1; **p<0.05; ***p<0.01

Note: Estimated paddy yield ATE and ATT are highlighted in boldface.

Table 6 presents the correlation test results for the validity of the IV in the 2SLS estimating ATE and ATT for rice yield and gross margin. The IV shows a strong and significant positive correlation with AC membership (Corr [IV, P]) in both yield and gross margin regressions, with coefficients of 0.14 and 0.13, respectively, significant at the 1% level. The correlations between the IV and the residuals (Corr [IV, e]) are negligible and not statistically significant, indicating that the IV is not correlated with the residuals in either regression. These findings suggest that the IV is both relevant and exogenous, thus supporting the reliability of the 2SLS estimates.

Table 6: Correlation test for IV validity

Correlation	Subset for yield regression		Subset for gross margin regression	
	ATE	ATT	ATE	ATT
Corr [IV, P]	0.14***	0.13***	0.14***	0.13***
Corr [IV, e]	- 0.01	- 0.00	0.03	- 0.03

*p<0.1; **p<0.05; ***p<0.01

4.4 Robustness check

Table 7 demonstrates the consistently positive impact of AC membership on yield and gross margin, as evidenced by ATE estimated through PSM, 2SLS, and ESR. The ATEs for yield are positive and statistically significant across all methods, highlighting a substantial improvement in yield due to AC membership. Similarly, the gross margin shows positive and significant ATEs across all methodologies, indicating a consistent enhancement in financial performance attributable to AC membership. This uniformity in results across PSM, 2SLS, and ESR underscores the robustness and reliability of the treatment effect, affirming the beneficial impact of AC membership on both agricultural output and financial performance. The methodological consistency strengthens the case for AC membership as a valuable intervention for small-scale rice farmers in Cambodia.

Table 7: Summary ATE and ATT estimated from the three methods

Methods	Yield (tons/ha)		Gross margin (10^3 riels/ton)	
	ATE	ATT	ATE	ATT
Observed	0.85***		134.83***	
PSM	0.87***	0.87***	112.97**	63.11
2SLS	0.49***	0.61**	110.21**	111.89
ESR	1.48***	1.43***	95.67***	83.21**

*p<0.1; **p<0.05; ***p<0.01

5 CONCLUSIONS

This study employed the 2SLS to evaluate the AC impact on rice yield and gross margin and utilised ESR to test the robustness of the results. The analysis revealed that AC membership increased rice yield by 0.49 tons per hectare and gross margin by 110.21 thousand riels per ton. When these benefits are aggregated and expressed in US dollars, they equate to an additional US$146 to the gross margin of a non-member's farm, marking a 73% improvement. In this study, gross margin represents the return to land and management as the opportunity costs of own labour and rice seed were accounted for. The estimated financial impact of AC membership represents a meaningful gain to small-scale rice farmers in Cambodia and lends support to policy interventions aimed at promoting the AC movement.

Despite the promising outcomes associated with AC membership, limited data prevent us from fully understanding the reasons behind the low participation rate among Cambodian farmers. This suggests the need for future studies to explore non-members' perspectives on ACs. For policymakers, our results underscore the importance of raising awareness to ensure that potential members understand the advantages of joining ACs. Accessibility to ACs among smallholders is another possible reason for the low participation rate. Including this variable in the subsequent agricultural surveys would benefit further studies in understanding the optimal number of ACs that should be increased to reach more smallholders.

Acknowledgement

I express my deepest gratitude to my PhD supervisors, Associate Professor Simeon Kaitibie and Associate Professor Michael Lyne, for their guidance, support, and valuable advice. I also thank the National Institute of Statistics (NIS) for releasing the national data essential for this study.

Reference

Abate, G. T., et al. (2014). Impact of agricultural cooperatives on smallholders' technical efficiency: Empirical evidence from Ethiopia. *Annals of Public and Cooperative Economics, 85*(2), 257-286. doi:10.1111/apce.12035

Abdul-Rahaman, A., & Abdulai, A. (2018). Do farmer groups impact on farm yield and efficiency of smallholder farmers? Evidence from rice farmers in northern Ghana. *Food Policy, 81*, 95-105. doi:10.1016/j.foodpol.2018.10.007

Abebaw, D., & Haile, M. G. (2013). The impact of cooperatives on agricultural technology adoption: Empirical evidence from Ethiopia. *Food Policy, 38*(1), 82-91. doi:10.1016/j.foodpol.2012.10.003

Ariyaratne, C. B., et al. (2006). What Determines Productivity Growth of Agricultural Cooperatives? *Journal of Agricultural and Applied Economics, 38*(1), 47-59. doi:10.1017/S1074070800022069

Bachke, M. E. (2019). Do farmers' organizations enhance the welfare of smallholders? Findings from the Mozambican national agricultural survey. *Food Policy, 89*, 101792. doi:10.1016/j.foodpol.2019.101792

Barrett, C. B., et al. (2012). Smallholder Participation in Contract Farming: Comparative Evidence from Five Countries. *World Development, 40*(4), 715-730. doi:10.1016/j.worlddev.2011.09.006

Blekking, J., et al. (2021). The benefits and limitations of agricultural input cooperatives in Zambia. *World Development, 146*, 105616. doi:10.1016/j.worlddev.2021.105616

CDRI. (2012). *Case study: Rice marketing value chains in Takeo province*. Retrieved from https://www.cdri.org.kh/storage/pdf/cdr13-2e-3_1617683350.pdf

Chagwiza, C., et al. (2016). Cooperative membership and dairy performance among smallholders in Ethiopia. *Food Policy, 59*, 165-173. doi:https://doi.org/10.1016/j.foodpol.2016.01.008

Chhinh, N., et al. (2022). Local engagement in the agricultural cooperatives (ACs) operation in Cambodia. *Sustainability, 14*(24). doi:DOI:10.3390/su142416515

FAOSTAT. (2024). Crops and livestock products. Retrieved from Crops and livestock products

Fischer, E., & Qaim, M. (2012). Linking Smallholders to Markets: Determinants and Impacts of Farmer Collective Action in Kenya. *World Development, 40*(6), 1255-1268. doi:10.1016/j.worlddev.2011.11.018

Gezahegn, T. W., et al. (2019). Big is efficient: Evidence from agricultural cooperatives in Ethiopia. *Agricultural Economics, 50*(5), 555-566. doi:10.1111/agec.12509

Glover, D. J. (1987). Increasing the benefits to smallholders from contract farming: Problems for farmers' organizations and policy makers. *World Development, 15*(4), 441-448. doi:10.1016/0305-750X(87)90112-4

Gujarati, D. (2003). *Basic econometrics*: McGraw-Hill.

Hao, J., et al. (2018). Cooperative membership and farmers' choice of marketing channels – Evidence from apple farmers in Shaanxi and Shandong Provinces, China. *Food Policy, 74*, 53-64. doi:10.1016/j.foodpol.2017.11.004

Heckman, J. J., et al. (1998). Matching As An Econometric Evaluation Estimator. *The Review of economic studies, 65*(2), 261-294. doi:10.1111/1467-937X.00044

Ho, D. E., et al. (2011). MatchIt: Nonparametric preprocessing for parametric causal inference. *Journal of statistical software, 42*(8), 1-28. doi:10.18637/jss.v042.i08

Hoken, H., & Su, Q. (2018). Measuring the effect of agricultural cooperatives on household income: Case study of a rice-producing cooperative in China. *Agribusiness (New York, N.Y.), 34*(4), 831-846. doi:10.1002/agr.21554

Iliopoulos, C. (2013). Public policy support for agricultural cooperatives: An organisational economics approach: Public policy support for agricultural cooperatives. *Annals of Public and Cooperative Economics, 84*(3), 241-252. doi:10.1111/apce.12012

ITC Trade Map. (2024). Trade statistics for international business development. Retrieved from Trade statistics for international business development

Ito, J., et al. (2012). Distributional effects of agricultural cooperatives in China: Exclusion of smallholders and potential gains on participation. *Food Policy, 37*(6), 700-709. doi:10.1016/j.foodpol.2012.07.009

Jiang, M., et al. (2024). Farmers' cooperatives and smallholder farmers' access to credit: Evidence from China. *Journal of Asian economics, 92*. doi:10.1016/j.asieco.2024.101746

Kelly, V., et al. (2003). Expanding access to agricultural inputs in Africa: a review of recent market development experience. *Food Policy, 28*(4), 379-404. doi:10.1016/j.foodpol.2003.08.006

Kumar, A., et al. (2018). Does cooperative membership improve household welfare? Evidence from a panel data analysis of smallholder dairy farmers in Bihar, India. *Food Policy, 75*, 24-36. doi:10.1016/j.foodpol.2018.01.005

Lin, B., et al. (2022). Impacts of cooperative membership on rice productivity: Evidence from China. *World Development, 150*, 105669. doi:10.1016/j.worlddev.2021.105669

Liu, Y., et al. (2018). The role of agricultural cooperatives in serving as a marketing channel: Evidence from low-income regions of Sichuan province in China.

Liu, Y., et al. (2019). The role of agricultural cooperatives in serving as a marketing channel: evidence from low-income regions of Sichuan province in China. *The international food and agribusiness management review, 22*(2), 265-282. doi:10.22434/IFAMR2018.0058

Ma, W., & Abdulai, A. (2016). Does cooperative membership improve household welfare? Evidence from apple farmers in China. *Food Policy, 58*, 94-102. doi:10.1016/j.foodpol.2015.12.002

Ma, W., & Abdulai, A. (2017). The economic impacts of agricultural cooperatives on smallholder farmers in rural China. *Agribusiness (New York, N.Y.), 33*(4), 537-551. doi:10.1002/agr.21522

Ma, W., & Abdulai, A. (2019). IPM adoption, cooperative membership and farm economic performance: Insight from apple farmers in China. *China agricultural economic review, 11*(2), 218-236. doi:10.1108/CAER-12-2017-0251

Ma, W., et al. (2018). Agricultural Cooperatives and Investment in Organic Soil Amendments and Chemical Fertilizer in China. *American Journal of Agricultural Economics, 100*(2), 502-520. doi:10.1093/ajae/aax079

Ma, W., et al. (2018). Agricultural cooperative membership and technical efficiency of apple farmers in China: An analysis accounting for selectivity bias. *Food Policy, 81*, 122-132. doi:10.1016/j.foodpol.2018.10.009

Ma, W., et al. (2022). Impacts of cooperative membership on banana yield and risk exposure: Insights from China. *Journal of Agricultural Economics, 73*(2), 564-579. doi:10.1111/1477-9552.12465

MAFF. (2022). *National Agricultural Development Policy*. Retrieved from Phnom Penh, Cambodia: https://data.opendevelopmentmekong.net/library_record/national-agricultural-development-policy-2022-2023/resource/6c9bf6f6-0d41-4779-8ea2-39d5e4011751

Manda, J., et al. (2020). Does cooperative membership increase and accelerate agricultural technology adoption? Empirical evidence from Zambia. *Technological forecasting & social change, 158*, 120160. doi:10.1016/j.techfore.2020.120160

Markelova, H., et al. (2009). Collective action for smallholder market access. *Food Policy, 34*(1), 1-7. doi:10.1016/j.foodpol.2008.10.001

Michalek, J., et al. (2018). The impact of producer organizations on farm performance: The case study of large farms from Slovakia. *Food Policy, 75*, 80-92. doi:10.1016/j.foodpol.2017.12.009

Mishra, A. K., et al. (2022). Helping feed the world with rice innovations: CGIAR research adoption and socioeconomic impact on farmers. *Global food security, 33*, 100628-100628. doi:10.1016/j.gfs.2022.100628

Mojo, D., et al. (2017). The determinants and economic impacts of membership in coffee farmer cooperatives: recent evidence from rural Ethiopia. *Journal of Rural Studies, 50*, 84-94. doi:10.1016/j.jrurstud.2016.12.010

Ngo, S., & Khon, L. (2023). *Assessment of the agricultural cooperatives for developing policy on public, private and producer partnership (PPPP) in Cambodia*. Phnom Penh: Centre for Policy Studies.

Nilsson, J. (2001). Organisational principles for co-operative firms. *Scandinavian journal of management, 17*(3), 329-356. doi:10.1016/S0956-5221(01)00010-0

Ortega, D. L., et al. (2019). Cooperative membership and coffee productivity in Rwanda's specialty coffee sector. *Food Security, 11*(4), 967-979. doi:10.1007/s12571-019-00952-9

Peng, Y., et al. (2022). Can cooperatives help commercial farms to access credit in China? Evidence from Jiangsu Province. *Canadian Journal of Agricultural Economics, 70*(4), 325-349. doi:10.1111/cjag.12320

Poulton, C., et al. (2010). The Future of Small Farms: New Directions for Services, Institutions, and Intermediation. *World Development, 38*(10), 1413-1428. doi:10.1016/j.worlddev.2009.06.009

Ravallion, M. (2007). Chapter 59 Evaluating Anti-Poverty Programs. In (Vol. 4, pp. 3787-3846): Elsevier B.V.

Sebhatu, K. T., et al. (2021). Exploring variability across cooperatives: economic performance of agricultural cooperatives in northern Ethiopia. *The international food and agribusiness management review, 24*(3), 397-420. doi:10.22434/IFAMR2019.0215

Sivramkrishna, S., & Jyotishi, A. (2008). Monopsonistic exploitation in contract farming: articulating a strategy for grower cooperation. *Journal of International Development, 20*(3), 280-296. doi:10.1002/jid.1411

The United Nations. (2017). The sustainable development report 2017. Retrieved from https://unstats.un.org/sdgs/files/report/2017/thesustainabledevelopmentgoalsreport2017.pdf

USDA. (2024). Rice sector at a glance. Retrieved from https://www.ers.usda.gov/topics/crops/rice/rice-sector-at-a-glance/

Vandeplas, A., et al. (2013). Multinationals vs. Cooperatives: The Income and Efficiency Effects of Supply Chain Governance in India. *Journal of Agricultural Economics, 64*(1), 217-244. doi:10.1111/1477-9552.12004

Verhofstadt, E., & Maertens, M. (2014). Smallholder cooperatives and agricultural performance in Rwanda: do organizational differences matter? *Agricultural Economics, 45*(S1), 39-52. doi:10.1111/agec.12128

Verhofstadt, E., & Maertens, M. (2015). Can Agricultural Cooperatives Reduce Poverty? Heterogeneous Impact of Cooperative Membership on Farmers' Welfare in Rwanda. *Applied economic perspectives and policy, 37*(1), 86-106. doi:10.1093/aepp/ppu021

Vuthy, T. (2020). The Supply of Fertiliser for Rice Farming in Takeo. In R. Cramb (Ed.), *White Gold: The Commercialisation of Rice Farming in the Lower Mekong Basin* (pp. 291-308). Singapore: Springer Nature Singapore.

Wang, Y., et al. (2013). Optimal caliper width for propensity score matching of three treatment groups: A Monte Carlo study. *PLoS One, 8*(12), e81045-e81045. doi:10.1371/journal.pone.0081045

Wassie, S. B., et al. (2019). Inclusiveness and effectiveness of agricultural cooperatives: recent evidence from Ethiopia. *International journal of social economics, 46*(5), 614-630. doi:10.1108/IJSE-07-2018-0340

Wollni, M., & Zeller, M. (2007). Do farmers benefit from participating in specialty markets and cooperatives? The case of coffee marketing in Costa Rica. *Agricultural Economics, 37*(2-3), 243-248. doi:10.1111/j.1574-0862.2007.00270.x