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Abstract

The recent renaissance of the Senegalese cooperative movement coupled with the revival of the agricultural sector motivated this study, which mainly aims to analyse the impact of farmer-based organization membership on household land productivity and net income. We combined the Propensity Score Matching (PSM) method with an Endogenous Switching Regression (ESR) model to derive treatment effects of membership in these farmer organizations using a national household-level survey data. Results exhibit consistency across estimations techniques. Estimates of both ESR and PSM models showed that membership in farmer organizations affects positively and significantly the household land productivity and net income. Moreover, findings show that membership has a heterogeneous impact. Households with the lowest probability to be member of farmer organizations have the highest impact. The effect of membership depends also on the specific type of organization.

Keywords: Farmer organizations, impact evaluation, land productivity, household income, Senegal.

JEL classification: Q13, D04, Q15, Q12.

1 Introduction

Agriculture is the main economic sector in Sub-Saharan Africa. However, its performances are challenged by many factors mainly the access to production inputs and technologies (World Bank, 2007). For decades, policymakers regarded collective action groups, such as farmers-based organizations or agricultural cooperatives, as important tools to address these challenges and improve agricultural performance (Salifu *et al.*, 2010). According to Schwettmann (2014), Sub-Saharan Africa cooperatives experienced several stages of development from the colonial era to post-structural adjustment programs or contemporaneous era. The contemporary cooperatives are less structured and economically less powerful compared to their predecessors, however, they are more diverse, more efficient and better adapted to local circumstances (Schwettmann, 2014).

The development approach based on farmers' collective action groups still prevails in many developing countries. For example, the Agricultural Services and Producer Organizations Projects implemented by the World Bank in Chad, Mali, and Senegal during the period 2000-2011, were mainly based on the development of farmer organizations, with the expectation that these farmer groups could influence and improve agricultural development and performances in these countries. Fortunately, nowadays, such an approach is increasingly supported by quantitative studies, in which scholars try to estimate the effective contribution of agricultural cooperatives membership to various agricultural indicators (technology adoption, commercialization, and marketing processes, farm performances, farmer welfare, etc.).

The literature on these studies in developing countries reveals that several factors are associated with the membership in farmer-based organizations, such as gender and age of farmers, assets possessed or wealth level (Bernard and Spielman, 2009; Fischer and Qaim, 2012; Abebaw and Haile, 2013; Mojo *et al.*, 2017), access to various rural institutions such as extension, credits and even cooperatives (Abebaw and Haile, 2013; Mojo *et al.*, 2017), off-farm activities, leadership, farming experience, geographic location (Abebaw and Haile, 2013), family size and social networks that farmers belong to, and education level (Mojo *et al.*, 2017). Meanwhile, membership in a cooperative or farmer organizations mostly affects positively and significantly the prices received by farmers (Wollni and Zeller, 2007; Bernard *et al.*, 2008; Bernard and Spielman, 2009), commercialization rates (Barham and Chitemi, 2009; Bernard and Spielman, 2009; Francesconi and Heerink, 2010; Fischer and Qaim, 2012; Chagwiza *et al.*, 2016), technologies adoption (Abebaw and Haile, 2013; Ma *et al.*, 2018), households welfare (Fischer and Qaim, 2012; Ito *et al.*, 2012;

Verhofstadt and Maertens, 2015; Ma and Abdulai, 2016; Mojo *et al.*, 2017; Ahmed and Mesfin, 2017; Mishra *et al.*, 2018).

Despite all these interesting findings, according to the recent study of Mojo *et al.* (2017), impact evaluation of the contribution of farmer-based organizations are still limited. Furthermore, some scholars have found no effect of membership in farmer-based organizations in their empirical work. Hoken and Su (2015) for instance did not observe any significant difference in received income between members and non-members of rice-producing cooperatives in suburban China. In addition, farmer-based organizations performance and impacts may vary across countries and regions even within the same agricultural sub-sector or across commodities (Bernard and Taffesse, 2012; Mojo *et al.*, 2017). Moreover, as pointed out by Verhofstadt and Maertens (2015) studies on cooperative organizations usually focus on a single cooperative or on multiple cooperatives in a single sub-sector. This study aims to contribute to this growing literature by taking advantage of an original country-wide survey data set collected in Senegal to quantify the effect of membership in farmer-based organizations[1] on farmers' land productivity and household incomes. The sample data used for the analysis comprises of 4245 farmers located in all six Senegalese agro-ecological zones. Looking at the effect of the farmers-based organizations at a country level gives a broader perspective of analysis, which is necessary for policy design.

Moreover, the Senegalese case study is of particular interest for several reasons. First, as argued by Reed and Hickey (2016), during the last decade, there has been a renaissance of cooperative movement due to several institutional changes. Second, since 2012, a sort of revival of the entire Senegalese agriculture is also observed, noted by the substantial increase of the sector's contribution to the national GDP from 12% in 2011 to 16% in 2017 (World Bank, 2017). Finally, in regards to quantitative analysis of the contribution of farmers organizations to agriculture, very little studies have been carried out in the case of Senegal. The remainder of this paper is organized as follows. The following sections describe the econometric framework and the data used. The last sections present, discuss and summarized the results of the estimations.

[1]We will use alternatively the expressions farmer organizations, farmer-based organizations (FBO), producer organizations, or agricultural collective action groups alternatively to define farmer-based organizations. Farmer organizations in our study include therefore all forms of organizations that provide farmers with farm or farm-related services as we will conceptualize later in the paper.

2 Econometric framework

2.1 Estimation strategy

Generally, a farmer decides to become a member of a farmer organization for the services provided by such a collective action group regarding access to credit, farm inputs, technologies, information, or marketing facilities. Therefore, a assumed rational farmer would choose to be a member of farmer organization if the expected utility from this organization membership (M_1) is greater than that from non-membership (M_0) . This utility gain from membership in a farmer-based organization $(M^* = M_1 - M_0)$ can be expressed as a function of an observable vector of covariates (Z) in a latent model as follows:

$$M_i^* = \alpha Z_i + \eta_i, \quad M_i = 1 \text{ if } M_i^* > 0, \tag{1}$$

where M_i is a binary variable that equals 1 if household i is a member of a farmer organization and zero otherwise; α is a vector of parameters to be estimated and Z_i is a vector of household demographics, socio-economic, and farm-level characteristics; and η_i is a random error term assumed to be normally distributed. Membership in a farmer organization is expected to affect various outcome variables at the farm or household level including land productivity and household income. Assuming that the outcome variable (land productivity or household income) is a linear function of a vector of exogenous variables X_i and endogenous membership in farmers organization M_i such that:

$$Y_i = \beta X_i + \delta M_i + \epsilon_i, \tag{2}$$

where Y_i represents the outcome variables (land productivity and agricultural income); M_i is defined as previously; β and δ are parameters to be estimated, and ϵ_i is the error term. However, farmers may self-select into FBOs, rather than being randomly selected. Therefore, estimating equation 2 using ordinary least square (OLS) might produce biased estimates. We explored then the propensity score matching and endogenous switching regression models to produce unbiased and consistent estimates. The PSM controls for selection bias through controlling for observable confounding factors. However, an important shortcoming of the PSM method is its inability to deal with biases resulting from unobservable characteristics of sampled units. The endogenous switching regression addresses the endogeneity of membership in farmers' organizations by accounting for both observed and unobserved sources of bias (Lokshin and Sajaia, 2004). Both are used to analyse the consistency of the obtained results across the estimation techniques

2.2 Propensity Score Matching (PSM)

The propensity score matching method (PSM) is a quasi-experimental technique often used in observational causal studies. PSM uses observable characteristics of observation units in the sample to generate a control group that is comparable to the treated group conditional on identified exogenous factors, but different regarding the intervention status, here membership in farmers organization (Rosenbaum and Rubin, 1983). PSM works under two main assumptions. The first is the conditional independence or unconfoundedness, stating that observable characteristics must be independent of potential outcomes, which implies that the membership decision is only based on observable characteristics of households. The second is the common support condition that needs to be satisfied, i.e. the distributions of observable characteristics between members of farmer organizations and non-members have to overlap (Jelliffe *et al.*, 2018). Empirically, in a first step, we regressed the membership of farmers organizations on a vector of observable variables Z (as in equation 1) to generate the propensity scores using a probit estimation (Hirano *et al.*, 2003). The estimated propensity scores ($PS_i = \text{Prob}\,(M_i = 1 \mid Z_i)$) represent the probability of a farmer to belong to a farmer-based organization, and the marginal effects express the impact of variables in Z on this probability. We included in Z a large set of conditioning factors in order to minimize omitted variables bias. Secondly, the generated propensity scores (PS) are used to match farmers who are members of FBOs to non-members. Numerous algorithms can be applied to match members and non-members of similar propensity scores. Furthermore, PSM methods are sensitive to a particular specification and matching method (Imbens, 2004; Caliendo and Kopeinig, 2008). Therefore, we use three different common matching techniques: the nearest neighbor matching, the kernel matching, and the radius matching. The nearest neighbor matching (NNM) algorithm was implemented with a caliper of 0.01. In a third step, we examined the extent of overall covariates balancing property and the overlap over the common support. The fourth step consisted of calculating the Average treatment on treated ATT, which is the mean difference between the two matched groups (Dehejia and Wahba, 2002; Imbens, 2004). Specifically, the estimated ATT is:

$$ATT(Z) = E\left[Y_1 \mid M = 1, \text{Prob}\,(Z)\right] - E\left[Y_0 \mid M = 1, \text{Prob}\,(Z)\right], \qquad (3)$$

where, Y_1 represents the outcome indicator of the members of farmers organizations, Y_0 is the outcome indicator of non-members; M is defined as previously. Finally, we checked the robustness of our estimates by using the Rosenbaum (2002) bounding approach. The main assumption behind matching is selection on observables. However, if there are unobserved variables that affect both membership and the outcome variable, a hidden bias might arise and affect the estimates of matching estimators (Rosenbaum, 2002). In particular, the hidden bias could lead to both positive and negative unobserved selection. Rosenbaum's method is based on the sensitivity parameter Γ that measures the degree of departure from random assignment of treatment. Two households with the same observed characteristics may differ in the odds of belonging to farmers organizations by at most a factor of Γ. Considering the upper bounds, the factors Γ are incrementally computed until the threshold of 10% of p-values is reached. The relatively higher is the Γ factor; the more robust is our model regarding hidden bias due to unobserved confounders. This sensitivity analysis is based on the Wilcoxon sign rank test. PSM analyses were conducted using STATA 14. Although we conducted these robustness checks, PSM only controls for selection biases from observed characteristics. We then applied an Endogenous switching regression analysis that has the potential to mitigate biases from both observable and unobservable factors.

2.3 Endogenous Switching Regression (ESR)

Under the Endogenous Switching Regression (ESR) framework, the impact of membership in farmer organizations on land productivity (and household income) is estimated in two stages: the first stage concerns the decision to join agricultural collective action groups (equation 1), and the second stage consists in the estimation of two regimes outcomes equations: one for members and another one for non-members (equations 4 and 5) represented as follows:

$$\text{Regime 1}: \quad Y_{1i} = \beta_1 X_i + \epsilon_{1i} \quad \text{if} \quad M_i = 1 \quad (\text{Members}) \tag{4}$$

$$\text{Regime 2}: \quad Y_{2i} = \beta_2 X_i + \epsilon_{2i} \quad \text{if} \quad M_i = 0 \quad (\text{Non} - \text{Members}), \tag{5}$$

where Y_1 and Y_2 represent the outcome respectively for farmer organization members (regime 1) and non-members (regime 2); X_i represents the vector of covariates of farmer i; β_1 and β_2 are parameters to be estimated; and ϵ_{1i} and ϵ_{2i} are errors terms associated with the outcomes variables. In the ESR framework, the error terms in the three equations (1, 5 and 4) are assumed to have a trivariate normal distribution, with zero mean and covariance matrix of the following form:

$$\operatorname{cov}(\eta, \epsilon_1, \epsilon_2) = \begin{bmatrix} \sigma_\eta^2 & \sigma_{\eta 1} & \sigma_{\eta 2} \\ \sigma_{1\eta} & \sigma_1^2 & . \\ \sigma_{2\eta} & . & \sigma_2^2 \end{bmatrix}, \tag{6}$$

where σ_η^2 is the variance of the error term in the selection equation (1); σ_1^2 and σ_2^2 are the variances of the error terms in the outcome equations (5 and 4); $\sigma_{1\eta}$ and $\sigma_{2\eta}$ are the covariances of η, ϵ_{1i} and ϵ_{2i}. Covariance between ϵ_{1i} and ϵ_{2i} is not defined since Y_1 and Y_2 are not observed simultaneously (Maddala *et al.*, 1986). The expected values of ϵ_{1i} and ϵ_{2i} conditional on the sample selection are non-zero, because the error term of equation 1 is correlated with the error terms of the outcome equations 5 and 4:

$$E\left[\epsilon_{1i} \mid M = 1\right] = \sigma_{1\eta} \frac{\left(\phi\left(Z_i \alpha\right)\right)}{\left(\Phi\left(Z_i \alpha\right)\right)} = \sigma_{1\eta} \lambda_{1i} \tag{7}$$

$$E\left[\epsilon_{2i} \mid M = 0\right] = \sigma_{2\eta} \frac{\left(\phi\left(Z_i \alpha\right)\right)}{\left(1 - \Phi\left(Z_i \alpha\right)\right)} = \sigma_{2\eta} \lambda_{2i} \tag{8}$$

where $\phi(.)$ is the standard normal probability density function; $\Phi(.)$ is the standard normal cumulative density function; and λ_{1i} and λ_{2i} are the inverse Mills Ratios (IMR) computed from equation 1 with $\lambda_{1i} = \frac{(\phi(Z_i\alpha))}{(\Phi(Z_i\alpha))}$ and $\lambda_{2i} = \frac{(\phi(Z_i\alpha))}{(1-\Phi(Z_i\alpha))}$, and included in equations 4 and 5 to correct for selection biases resulting from unobservable factors. Therefore, we have:

$$Y_{1i} = \beta_1 X_i + \sigma_{1\eta} \lambda_{1i} + \delta_{1i} \quad \text{if} \quad M_i = 1 \quad (\text{Members}) \tag{9}$$

$$Y_{2i} = \beta_2 X_i + \sigma_{2\eta} \lambda_{2i} + \delta_{2i} \quad \text{if} \quad M_i = 0 \quad (\text{Non} - \text{Members}), \tag{10}$$

where δ_{1i} and δ_{2i} are error terms with conditional zero means. The full information maximum likelihood (FIML) method was applied to have consistent estimates (Greene, 2000; Lokshin and Sajaia, 2004). Furthermore, appropriate identification of ESR requires at least one variable in Z that does not appear in X. This variable represents the exclusion restriction necessary to fully estimate the model. The estimation of the selection equation (1) thus includes two potential instruments. A valid instrument is required to influence the farmer's choice of membership but does not have any direct effect on the outcomes of interest. The first potential instrument that we use is whether farmers receive information on sales. Thus, from the question "do you receive information on sales", we created a dummy variable "Information on sales" which takes a value of 1, if the farmer receives information on sales and the value 0, otherwise. This instrument is supposed to correlate significantly with the membership in FBOs. Those farmers who receive information on sales have a higher probability to belong to farmer organizations. Farmers could join these organizations with the motivation to be more informed on sales and the associated better prices. However, receiving this information is not supposed to directly affect the outcome variables of interest since only receiving information does not directly improve or decreases the land productivity nor total household incomes (but indirectly affects both outcomes through membership in the organization). The second potential instrument is the main type of water source used by the household. Similarly to the first instrument, from the question: "what is your main source of drinking water ?", we created a dummy variable "water source" that takes the value of 1, if the household uses tap water and the value of 0, otherwise. The use of tap water is an asset variable that expresses the capacity of the household to be a member of farmer organizations, the capacity to afford membership fees.

To check for the validity of these instruments, we ran a probit model for the equation 1 and OLS regressions for outcome equations (4 and 5) separately and checked in which equation these variables are effectively significant. The results are presented in appendix table 11. The positive coefficients of variable "Information on sales" and "Source of water" confirms the expectation that households who have access to information on sales and use tap water are more likely to be members of farmer organizations. The designed instruments significantly influence the membership in FBOs but not the non-members farmers' land productivity ($F = 0.084$ (2), p-value $= 0.920$) and household net income ($F = 0.838$ (2), p-value $= 0.433$).

From the assumptions on the distribution of the error terms (6), the derived log-likelihood function is specified as:

$$\ln L = \sum_{i=1}^{N} \left\{ A_i \left[\ln\phi \left(\frac{\epsilon_{1i}}{\sigma_1} \right) - \ln\sigma_1 + \ln\Phi\left(\theta_{1i}\right) \right] + \right. \tag{11}$$

$$\left. (1 - A_i) \left[\ln\phi \left(\frac{\epsilon_{2i}}{\sigma_2} \right) - \ln\sigma_2 + \ln\left(1 - \Phi\left(\theta_{2i}\right)\right) \right] \right\}, \tag{12}$$

where $\theta_{ji} = \frac{(Z_i\alpha + (\rho_j \epsilon_{ji})\sigma_j)}{\sqrt{1-\rho_j^2}}$, with $j = 1, 2$ and ρ_j ($\rho_1 = \frac{\sigma_{1\nu}^2}{\sigma_\nu}\sigma_1$ and $\rho_2 = \frac{\sigma_{2\eta}^2}{\sigma_\eta}\sigma_2$) being the correlation coefficients between the error term η_i of the selection equation (1) and respectively the error terms ϵ_{1i} and ϵ_{2i} of the outcome equations (4 and 5). If one of the estimates of correlation coefficients ρ_1 or ρ_2 is statistically significant, this would indicate the existence of a selectivity bias due unobserved factors (Abdulai and Huffman, 2014). Then, the endogenous switching regression model would be appropriate. When $\rho_1 > 0$, this implies a negative selection bias, indicating that farmers who have below than average outcomes are more likely to choose to be members of farmer organizations, whereas with $\sigma_{1\nu} < 0$, this would suggest a positive selection bias. Moreover, if ρ_1 or ρ_2 have alternate signs, then farmers choose to be members of producer organizations based on their comparative advantage: members have above-average outcomes from membership status and the non-members have above-average outcomes from being non-members. If these correlation coefficients have the same sign, it would mean a hierarchical sorting: members have above-average outcomes whether they are members or not, but they are better off being members, while non-members have below-average outcomes in either case, but they are better off not being members. The coefficients from the ESR model allow one to derive the average treatment effect on the treated (ATT). Specifically, the observed and unobserved counterfactual outcomes for farmer organization members can be computed as:

$$E\left[Y_{1i} \mid M=1\right] = \beta_1 X_i + \sigma_{1\eta}\lambda_{1i} \tag{13}$$

$$E\left[Y_{2i} \mid M=0\right] = \beta_2 X_i + \sigma_{2\eta}\lambda_{2i} \tag{14}$$

$$E\left[Y_{2i} \mid M=1\right] = \beta_2 X_i + \sigma_{2\eta}\lambda_{1i} \tag{15}$$

$$E\left[Y_{1i} \mid M=0\right] = \beta_1 X_i + \sigma_{1\eta}\lambda_{2i} \quad . \tag{16}$$

Equation 13 computes the observed outcome (a) for organization members and equation 14 calculates the observed outcome (b) for non-members. The expected outcome (c) in equation 15 represents the counterfactual for the observed outcome (a) in equation 13. This counterfactual expresses what would have happened had the farmers decided to be member of the organizations. Similarly the equation 16 is a counterfactual outcome (d) for the observed outcome (b) in equation 14. It represents the scenario in which farmers decided to be members of producers organizations. Using these expected outcomes (equations 13 to 16) we derive unbiased treatment effects: the average treatment effect on treat (ATT, which is the difference between equation 13 and 15 that is a − c), and the average treatment effect on untreated (ATU, which is the difference between equation 16 and 14 that is d − b).

$$ATT = E\left[Y_{1i} \mid M=1\right] - E\left[Y_{2i} \mid M=1\right] = \left(\beta_1 - \beta_2\right) X_i + \lambda_{1i}\left(\sigma_{1\nu} - \sigma_{2\nu}\right) \tag{17}$$

$$ATU = E\left[Y_{1i} \mid M=0\right] - E\left[Y_{2i} \mid M=0\right] = \left(\beta_1 - \beta_2\right) X_i + \lambda_{2i}\left(\sigma_{1\nu} - \sigma_{2\nu}\right). \tag{18}$$

2.4 Addressing other empirical issues

For the empirical specification of the first stage of the ESR model (estimation of the selection equation), several factors are associated with membership in producer organizations. These factors which include personal details of household head (gender, age, education), household characteristics (e.g. household size, agricultural assets, land size), access to agricultural extension services, and the geographic location of the household. It is worth noting however, that households could have better access to extension due to their membership in collective action groups, rendering the access to extension services variable potentially endogenous in the modeling of the choice to farmers organizations and leading then to biased estimates. We, therefore, corrected this endogeneity issue with the two-stage control function approach suggested by Wooldridge (2015). In a first stage, we estimated separately, the access to extension services and the membership in organizations on the same independent variables plus an instrument, here the farmer's expressed needs of extension services, using a probit model. The instrument, "need of extension"[2], significantly influences the access to extension services (χ^2 (1) = 3.613, p-value = 0.057) but not directly the household decision to belong to organizations (χ^2 (1) = 0.647, p-value = 0.421, see table 9 in the appendix). In the second-stage probit estimation, the access to extension services variable and their generalized residuals predicted from the first-stage are included in the selection equation. Moreover, this variable "extension needs" is not correlated to the other instruments used in the rest of the analysis, such as information on sales (Pearson's correlation = 0.011, t = 0.741 (4243), p-value = 0.459) or the use of tap water for drinking (Pearson's correlation = -0.005, t = -0.353 (4243), p-value = 0.724)

2.5 Heterogeneous treatment effects analysis

Following (Abebaw and Haile, 2013) and (Verhofstadt and Maertens, 2015), we analyse how the estimated outcome effects of organizations membership vary within members. Therefore, we used the estimates of ATT as a dependent variable and run ordinary least squares (OLS) to regress it on farm household characteristics. In addition, we plotted OLS regressions of estimated ATT on the propensity score, and

[2]From the two questions: "do you need extension services?" and "what do you need extension services for?", we created a dummy variable "extension needs" which takes the value 1, if the household responds "yes" to the first question and states technology diffusion services in the second question and the value 0, otherwise. Farmers who expressed a need for technologies in their activities are expected to have access to extension services, or at least exploring ways to have access to it.

on some farm characteristics (i.e. age, education, gender, size of the household, and distance to nearest road) to derive smoothed curves. Such graphical and statistical analyses help to find out which type of households the impact of membership in farmer organizations is the most important.

3 Data sources and descriptive statistics

3.1 Data sources

The data used for the analysis derived from a survey conducted in Senegal, which randomly sampled 4480 households that mainly produce dry cereals (or rainfed cereals). The survey was done under the Agricultural Policy Support Project (Projet d'Appui aux Politiques Agricoles, PAPA)[3], which is an initiative of the Government of Senegal funded by USAID-Senegal as part of the "Feed The Future" initiative, and implemented for a period of 3 years (2015 - 2018) by the Senegalese Ministry of Agriculture and Rural Facilities with technical support from the International Food Policy Research Institute (IFPRI). A multistage sampling procedure was applied for the selection of households and a structured household questionnaire was used to collect information. This questionnaire included several modules and gathered information on a range of topics such as household demographic and socioeconomic characteristics, farmer organization membership, household assets, crop production, livestock revenues, income and expenditures, access to infrastructure, access to institutions, commercialization, and production shocks and risk management strategies. Besides information on crop production and inputs used, data collection also included market prices and households' adoption of agricultural technologies during the main agricultural season of 2016/2017. After data cleaning and removing observations with no information on the different outcome variables, a final sample of 4245 households was used for the analysis. This sample includes farmers located in all six Senegalese agro-ecological zones.

3.2 Descriptive statistics

Table 1 presents the definition and summary statistics of the variables used in the analysis. It also reports the comparative descriptive statistics of these variables based on farmer organization membership status. Following the definition of Bernard

[3]Official website of the project is http://www.papa.gouv.sn/.

et al. (2015), our variable of interest "organization membership" is referred to as membership in a rural producer organization that provides farmers with farming and farm-related services including access to inputs, markets and credits, collective sales, and capacities reinforcement. Eight types of farmers organizations were mentioned by the surveyed households: Producer Groups, Economic Interest Groups, Rural Associations, Cooperatives, Women Producers Groups, Federations, Unions, and Networks. Therefore, the variable "organization membership" is binary, coded as 1 if a member of the household belongs to any of this farmers-based organization, and 0 otherwise. In some households, several family members expressed their belonging to these organizations, with a maximum of 7 members. However, on average only one family member belongs to a group. About 9% of the households in the sample have at least one person belonging to a group. The main organizations, which gather most of the household family members, are Economic Interest Groups (44.1%), Rural Associations (16.7%), Producer Groups (16.1%), and Cooperatives (15.3%).

Regarding the outcome variables, land productivity is measured as the net value in FCFA[4] of all crop outputs valued at the market prices per unit of land area. This approach is more suitable since most cereals productions are not marketed by farmers. The net value of all crop production represents the value of all crop production after the deduction of all crop production costs, such as seeds cost, fertilizer costs, all other costs, and hired labour. Farmers in the sample have on average a land productivity of 130,050 FCFA per hectare. The household income was generated by adding to the net value of all crop production, the livestock income received by the farmer during the last 12 months, and all off-farm incomes [5]. On average, the sampled households receive 592,100 FCFA as net total income. The two outcomes variables are log specified.

[4] 1 FCFA=0.0017 USD as at December 2019.

[5] Crafts, hunting, forestry, fishing, small business, farm products processing, transport

Table 1: Description of variables

Variables	**Description and measurement**	**Pooled** (1)	**Members** (3)	**Non-Members** (2)	**P-values** (4)
Organization Membership	Membership in farmer organizations (1=yes, 0=no)	0.088 (0.28)			
	Outcome variables				
Land Productivity	All crop production per hectare (1000 FCFA/ha)	130.05 (301.62)	255.75 (631.57)	117.97 (244.60)	<0.01
Household income	Total net household income (1000 FCFA)	592.10 (878.51)	844.09 (1299.84)	567.90 (823.01)	<0.01
	Household and Head characteristics				
Gender	Household head is a male (1=yes, 0=no)	0.93 (0.25)	0.95 (0.22)	0.93 (0.25)	0.14
Age	Age of household head (years)	53.07 (13.44)	51.09 (12.13)	53.27 (13.55)	<0.01
Education	Formal education (1=yes, 0=no)	0.37 (0.48)	0.51 (0.50)	0.36 (0.48)	<0.01
Active members	Active family members	5.72 (3.15)	6.37 (3.43)	5.66 (3.12)	<0.01
Dependents	Non-active family members	4.28 (3.31)	5.01 (3.82)	4.21 (3.25)	<0.01
Migration	Household head is a migrant (1=yes, 0=no)	0.14 (0.35)	0.15 (0.36)	0.14 (0.35)	0.51
	Household Assets				
Equipment	Agricultural Equipment (1.000.000 FCFA)	0.13 (0.56)	0.17 (0.46)	0.13 (0.57)	0.08
Area Owned	Land size owned by household (ha)	5.82 (8.37)	5.62 (6.24)	5.84 (8.54)	0.52
	Access to infrastructures				
Distance to road	Distance to nearest all-weather road (km)	10.15 (14.15)	10.32 (13.90)	10.14 (14.18)	0.81
Extension	Access to extension services (1=yes, 0=no)	0.11 (0.31)	0.42 (0.49)	0.08 (0.27)	<0.01
	Agro-ecological zones				
Groundnut AEZ	Groundnut agro-ecological zone (1=yes, 0=no)	0.50 (0.50)	0.28 (0.45)	0.52 (0.50)	<0.01
Casamance AEZ	Casamance agro-ecological zone (1=yes, 0=no)	0.25 (0.43)	0.31 (0.46)	0.25 (0.43)	0.01
South-East AEZ	South East agro-ecological zone (1=yes, 0=no)	0.11 (0.31)	0.15 (0.36)	0.11 (0.31)	0.02
Other AEZ	Other agro-ecological zones (1=yes, 0=no)	0.14 (0.35)	0.25 (0.44)	0.13 (0.34)	<0.01
	Instrumental Variables				
Information on Sales	Information on Sales (1=yes, 0=no)	0.01 (0.11)	0.05 (0.22)	0.01 (0.10)	<0.01
Tap water	Use of tap water for drinking (1=yes, 0=no)	0.35 (0.48)	0.36 (0.48)	0.35 (0.48)	0.65
Extension needs	Express need for technologies (1=yes, 0=no)	0.01 (0.09)	0.01 (0.07)	0.01 (0.09)	0.37
N	Number of Observations	4245	372	3873	4245

Note: Standard deviations are in parenthesis

Following the literature on land productivity and agricultural household incomes, we have included in the models, several control variables, such as household and its heads characteristics (gender, age, education, active household size, dependents[6], and migration status[7]), the household assets (the total value of possessed agricultural equipment and the land area owned), household access to rural institutions (extension services, distance to the nearest road), and agro-ecological zones dummies. About 93% of the households in the sample are predominantly male-headed. The sampled households heads are generally old with an average age of 53 years and without any formal education. Besides farming activities, households also get revenues from off-farm activities (33.8%). On average, the household includes ten family members and owns about 130,000 FCFA of agricultural implements and about 5.82 ha of farming land with 4.47 ha dedicated to crop cultivation. More than 85% of farm households in the sample are located in the Groundnut basin, Casamance and South East agro-ecological zones.

When comparing members of farmer organizations to non-members, significant differences in means can be observed for outcome indicators as for most of the control variables. Members of farmer organizations tend to have larger households (11 persons) than non-members (9 to 10 persons), and they appear averagely to be more educated. They also have better productivity per hectare and receive higher incomes than non-members. These significant differences in means between members and non-members suggest that farmers-based organizations might play an important role in enhancing farmers' adoption of technologies and permitting them to have a higher level of productivity and incomes. However, these results does not permit making inferences about the effect that membership in farmers organizations might have on farmers' incomes. These comparisons of means do not account for confounding factors such as observed household and farm-level characteristics and unobserved factors (e.g. perception and motivations of membership choice).

4 Results and discussion

This section reports first the identified factors that drive membership in farmers' organizations using the probit regression model. Then, it is followed by the results of the impact of organization membership on land productivity and income using

[6]Active members are aged between 15 and 65 years and dependents regroup members aged below 15 years and more than 65 years.

[7]It is a dummy variable for the migration status of the household head. This variable also serves as a proxy for involvement in off-farming activities.

the PSM and ESR models. Finally, the heterogeneous effects are analyzed and discussed.

4.1 Membership in farmers organizations

Factors that influence households' decision to belong to farmer organizations are presented in table 2 with their marginal effects. The likelihood ratio test shows that the model estimates are significant at 1% level ($\chi^2 = 445.49\ (17),\ \mathrm{p} < 0.01$). Results of estimation of equation 1 indicate that membership in farmer organizations is significantly influenced by the education level of the household head, the household's size (number of active persons living in the household and the dependents), distance of the household to the nearest road, access to information on sales, the existence of tap water in the household and the location of the household in different agro-ecological zones (Groundnut basin, Casamance and South-East).

Formal education significantly and positively affects the probability for a household to be a member of an agricultural collective action group. Households with an educated head are about 4% more likely to join agricultural collective action groups. The household family size has also a positive and significant effect on membership in farmer organizations. These results support those of Bernard and Spielman (2009) and Ma and Abdulai (2016). For instance, households that have more active persons in the household have a higher probability (0.4%) to be members of producer organizations. With more active people, households have a better chance that one of their family members could belong to a farmer-based organization.

Geographic location and agro-climatic conditions of the households also have significant effects on the decision of farmers to be members or not. Results reveal that farmers who live closer to all-weather roads are respectively better prone to participate in groups actions with a 0.1% probability for each additional kilometre. These results suggest a clustering of farmers' organization members, due to spatial non-observable factors such as climate, institutions, and infrastructure. These findings corroborate those of Abebaw and Haile (2013) and Ma and Abdulai (2016). According to Ma and Abdulai (2016), in China variables representing soil types and regions have significant cluster effects.

Gender of the household head and the different assets owned by the household such as the value of agricultural implements and the land area do not appear to have any significant effect on membership, contradicting with some of the previous studies by Abebaw and Haile (2013) and Mojo *et al.* (2017). In addition, access to extension services affect positively but not significantly the farmers' probability to be members of collective action organizations. However, the effect appears significant in the ESR regressions. Access to various institutions e.g. agricultural extension services (Abebaw and Haile, 2013) and credit (Abdul-Rahaman and Abdulai, 2018) and even the access to farmer organizations Mojo *et al.* (2017) are, in previous literature associated with membership.

Table 2: Probit Estimation of Membership in Farmers Organizations

	Coefficients	Marginal Effets
Intercept	-1.868 (0.450)***	
Gender	0.060 (0.133)	0.007 (0.014)
Age	0.024 (0.017)	0.003 (0.002)
Age Squared	-0.000 (0.000)**	-0.000 (0.000)**
Education	0.314 (0.078)***	0.040 (0.010)***
Active persons	0.033 (0.010)***	0.004 (0.001)***
Dependents	0.027 (0.010)***	0.003 (0.001)***
Migration	0.042 (0.101)	0.005 (0.013)
Equipment	-0.009 (0.050)	-0.001 (0.006)
Area owned	0.002 (0.004)	0.000 (0.000)
Distance to road	-0.008 (0.003)***	-0.001 (0.000)***
Extension	0.286 (0.832)	0.040 (0.136)
Groundnut AEZ	-0.892 (0.154)***	-0.109 (0.020)***
Casamance AEZ	-0.318 (0.123)***	-0.033 (0.011)***
South-East AEZ	-0.280 (0.118)**	-0.028 (0.010)***
Information on Sales	0.801 (0.292)***	0.162 (0.085)*
Tap water	0.196 (0.076)***	0.024 (0.010)**
Extension residuals	0.437 (0.437)	
Log Likelihood	-1038.128	-1038.128
LR Test	445.49***	
Num. obs.	4245	4245

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

4.2 Impact of FBO membership: PSM results

This section presents the treatment effects estimated from the PSM models. Based on the probit estimation of equation 1, propensity scores were obtained for the matching. The validation of PSM models depends on the quality of the matching. Table 10 in appendix provides the overall covariate balancing test. Results show that the standardized mean difference for all covariates used for the matching reduces from 23.9% before matching to 2.7% after matching. Moreover, the likelihood ratio test indicates that the null hypothesis of the joint significance of all covariates could be rejected before matching p > $\chi^2 = 0.000$. Conversely, after the matching, with the same test the joint significance of all covariates could not be rejected p > $\chi^2 = 0.997$. These results indicate that the required balancing property of the distribution of propensity scores is satisfied. Furthermore, Figure 2 in the appendix shows the common support between the two groups. Most of farmers organizations members and non-members had a common support region, only seven members were outside the common support region and therefore dropped from the matched sample.

Table 3 reports the average treatment effect on the treated from the PSM models. The robust standard errors of these estimates were calculated by bootstrapping using 50 replications. As stated previously three matching methods were used: the nearest neighbor matching, the kernel matching, and the radius matching. The average treatment effects on the treated for land productivity and household income are all positive and statically significant. For instance, with the Nearest Neighbour matching method, the effects of membership are evaluated at 28% for land productivity and 14.4% for household income. The estimated values of the effect of membership of producer organizations are quite close across the alternative matching specifications. From these results, one can conclude that that in the absence of observable selection bias, membership in a collective action group affects positively and significantly farmers' land productivity and household income. Our findings are similar to those of other studies that empirically reported a significant and positive relationship between membership in farmer-based organizations and farm productivity and household welfare, in China (Ma and Abdulai, 2016) and in Rwanda (Verhofstadt and Maertens, 2014).

Table 3: ATT of FBO membership: PSM Estimates

Outcomes	Matching Methods		
	Nearest Neighbor	Kernel	Radius
Land Productivity	0.280 (0.072)***	0.323 (0.067)***	0.331 (0.050)***
Household Income	0.144 (0.081)*	0.182 (0.073)**	0.183 (0.070)***

Notes: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Robust standard errors are in parentheses.

To check the robustness of our PSM model results, as mentioned previously, we calculated the Rosenbaum bounds (Becker and Caliendo, 2007) and reported in table 4 the upper bounds results with their p-values. The Rosenbaum bounds were computed for treatment effects that are significantly different from zero. Considering the significance level of 10%, the lowest value of Γ in all PSM specifications was $1.10 - 1.15$ obtained with the nearest neighbour technique and the largest value was $1.70 - 1.75$ observed for a kernel matching. For instance, when considering the impact of membership on land productivity (for PSM Nearest Neighbour), the sensitivity analysis implies that at a level of $\Gamma = 1.50$, the causal inference may be viewed critically. This would mean that if farmers with similar covariates differ in their odds of being members of farmer-based organizations by a factor of 50%, the significance of membership effect on land productivity might be questionable. This value is relatively low. Considering the threshold of 80% for Γ, which is generally used in social sciences. These results suggest that the positive and significant impact estimates of organization membership on land productivity and household incomes are at some levels sensitive to unobservables or hidden-bias. Therefore, we considered the endogenous switching regression approach that accounts for both observed and unobserved factors.

Table 4: Rosenbaum Γ bounds sensitivity analysis for hidden bias

Outcomes	Matching Methods		
	Nearest Neighbor	Kernel	Radius
Land Productivity	$1.45 - 1.50$ ($0.066 - 0.109$)	$1.70 - 1.75$ ($0.089 - 0.131$)	$1.65 - 1.70$ ($0.084 - 0.127$)
Household Income	$1.10 - 1.15$ ($0.055 - 0.109$)	$1.20 - 1.25$ ($0.059 - 0.110$)	$1.20 - 1.25$ ($0.090 - 0.157$)

Notes: P-values are in parenthesis

4.3 Impact of FBO membership: ESR results

Results from the endogenous switching regression models are presented in tables 5and 6. The ESR models were estimated using the FIML approach which derives both the selection and outcome equations jointly. The first stages of the estimation of ESR regressions are presented in columns (1) while the second stage of the estimation, i.e. estimation of separate outcome equations for organizations members and non-members, are reported in columns (2) and (3).

Except for the variables access to extension services and information on sales, the estimation results of the selection equation are similar, in terms of signs and significance, to the estimation of the probit estimation of equation 1 discussed previously. The exclusion restriction variable, access to information on sales, is statistically significant only for the household income model. Meanwhile, the second stage of the FIML shows that the estimated coefficients of the correlation ρ between farmer organizations membership and both land productivity and household income are all negative, but statistically significant only for members, implying that the hypothesis of absence of sample selectivity bias, in both models may be rejected. These findings suggest that both observed and unobserved factors influence the decision to belong to farmers organization and both land productivity and household income given the membership. Moreover, ρ_1 (members correlation coefficients) in both outcome models have a negative sign, indicating a positive selection bias and implying that households with above average land productivity and household income are more likely to belong to farmer-based organizations. Furthermore, ρ_1 and ρ_2 have the same sign, suggesting that members have above-average land productivity and household income whether they are members or not, but they are better off being members, while non-members have below-average outcomes in either case, but they are better off not being members.

Table 5: ESR Regression of Land Productivity

	Selection Equation	Members	Non-Members
	(1)	(2)	(3)
Intercept	-1.808 (0.441)***	15.829 (0.894)***	11.035 (0.213)***
Gender	0.037 (0.131)	-0.027 (0.242)	0.090 (0.060)
Age	0.017 (0.016)	-0.049 (0.028)*	-0.002 (0.007)
Age Squared	-0.000 (0.000)*	0.001 (0.000)**	0.000 (0.000)
Education	0.245 (0.073)***	-0.364 (0.120)***	0.120 (0.033)***
Active persons	0.034 (0.010)***	-0.004 (0.020)	0.016 (0.006)***
Dependents	0.029 (0.010)***	-0.036 (0.018)**	-0.003 (0.005)
Migration	-0.023 (0.096)	-0.130 (0.153)	-0.063 (0.044)
Equipment	-0.042 (0.052)	0.173 (0.131)	0.079 (0.027)***
Area owned	0.001 (0.004)	-0.019 (0.010)*	-0.007 (0.002)***
Distance to road	-0.007 (0.003)***	-0.004 (0.005)	-0.004 (0.001)***
Extension	1.399 (0.702)**	-0.712 (0.207)***	0.250 (0.066)***
Groundnut AEZ	-0.762 (0.140)***	-0.597 (0.203)***	-0.232 (0.056)***
Casamance AEZ	-0.255 (0.116)**	-0.764 (0.177)***	0.361 (0.056)***
South-East AEZ	-0.283 (0.118)**	-1.008 (0.208)***	0.358 (0.068)***
Information on Sales	0.287 (0.254)		
Tap water	0.180 (0.066)***		
Extension residuals	-0.158 (0.369)		
σ_1		1.375 (0.127)***	
σ_2			0.936 (0.011)***
ρ_1		-0.868 (0.046)***	
ρ_2			-0.057 (0.093)
Log Likelihood	-6754.896		
Num. obs.	4245	372	3873

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

Outcomes equations from the ESR regressions show that members land productivity is significantly determined by the age, education, number of dependents, area of land owned, access to extension, and the household agro-ecological zone (Groundnut basin, Casamance and South East). For non-members, the main variables that

Table 6: ESR Regression of Household Income

	Selection Equation (1)	Members (2)	Non-Members (3)
Intercept	-1.864 (0.444)***	14.675 (0.985)***	11.454 (0.255)***
Gender	0.053 (0.132)	0.700 (0.254)***	0.528 (0.072)***
Age	0.020 (0.017)	-0.039 (0.030)	0.003 (0.009)
Age Squared	-0.000 (0.000)*	0.000 (0.000)	-0.000 (0.000)
Education	0.267 (0.075)***	-0.196 (0.132)	-0.025 (0.039)
Active persons	0.035 (0.010)***	0.021 (0.021)	0.055 (0.007)***
Dependents	0.027 (0.010)***	-0.032 (0.019)	0.020 (0.006)***
Migration	0.011 (0.098)	-0.106 (0.160)	-0.100 (0.052)*
Equipment	-0.027 (0.051)	0.315 (0.153)**	0.135 (0.033)***
Area owned	0.003 (0.004)	0.061 (0.011)***	0.037 (0.002)***
Distance to road	-0.007 (0.003)***	-0.007 (0.005)	-0.007 (0.001)***
Extension	1.001 (0.756)	-0.791 (0.243)***	0.248 (0.084)***
Groundnut AEZ	-0.807 (0.146)***	0.605 (0.228)***	0.013 (0.068)
Casamance AEZ	-0.267 (0.119)**	0.028 (0.188)	0.135 (0.066)**
South-East AEZ	-0.278 (0.119)**	0.140 (0.218)	0.256 (0.081)***
Information on Sales	0.581 (0.270)**		
Tap water	0.180 (0.070)**		
Extension residuals	0.057 (0.397)		
σ_1		1.349 (0.150)***	
σ_2			1.117 (0.013)***
ρ_1		-0.796 (0.081)***	
ρ_2			-0.054 (0.113)
Log Likelihood	-7473.406		
Num. obs.	4245	372	3873

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

affect significantly their land productivity are education, number of active family people, the value of agricultural equipment, area of land owned, distance to the nearest road, access to extension services, the residence in agro-ecological zones (Groundnut, Casamance and South East).

Results of the ESR also exhibit some differences in the determinants of household income for members and non-members. Variables such as gender, the value of agricultural equipment, land area owned, access to extension services, and the residence in Casamance agro-ecological zone, affect significantly members household income. Meanwhile, the household income of non-members is influenced by gender, household size, migration, agricultural equipment, area of land owned, distance to road, access to extension services, residence in the Casamance and South-East agro-ecological regions.

The ESR model produces mean outcomes on treated household and corresponding counterfactual outcomes i.e. what would have been the outcome had the treated group not received the treatment. The average treatment effect on treated (ATT) is the net difference between these two outcomes. Similarly, the model also produces the mean outcome of the control group (non-members) and its counterfactual i.e. what would have been the mean outcome had the control group received the treatment. The difference between these last two outcomes produces the average treatment effect on untreated (ATU). These average outcomes and the estimated ATT and ATU are presented in table 7. The estimates reveal that the treatment effect for membership in farmer-based organizations on land productivity and household income are positive and significantly different from zero. The ATT are 2.405 and 1.959 for land productivity and household income, respectively. Membership in producer organizations significantly improves the log of land productivity and household income by 19.3% and 14.1%, respectively. Had non-members decided to be members of farmer-based organizations, the log of their land productivity would have been increased by 24.5% and their income by 20%.

Table 7: ATT and ATU of FBO membership: ESR Estimates

Outcomes	Mean outcomes		Treatment Effect	Effect(%)
	Members	Non-Members		
Land Productivity	14.842 (0.724)	12.438(0.265)	$ATT = 2.405\ (0.769)^{***}$	19.3
	13.416 (0.588)	10.774(0.260)	$ATU = 2.643\ (0.692)^{***}$	24.5
Household Income	15.899 (0.977)	13.940 (0.486)	$ATT = 1.959\ (0.686)^{***}$	14.1
	14.629 (0.856)	12.194 (0.455)	$ATU = 2.435\ (0.601)^{***}$	20.0

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

Our results suggest that farmer organizations in Senegal are effective at enhancing farmers' land productivity and welfare. These results are in line with those of Ma and Abdulai (2016) in China, Mishra *et al.* (2018) in Nepal, and Francesconi and Ruben (2012) in Ethiopia, who found that members of farmer-based organizations generally experience better crop yields than non-members. Our findings are also consistent with the results of the growing literature on farmer-based organizations in developing countries, where most scholars observed a positive correlation between membership and economic welfare (Fischer and Qaim, 2012; Verhofstadt and Maertens, 2015; Wossen *et al.*, 2017).

4.4 Heterogeneous treatment effects

For the rest of the analysis, we focus on the evaluation of the heterogeneity of the effect of membership in farmer organizations, using graphical and regressions techniques. Figure 1 shows how the treatment effect on land productivity and household income (estimated from ESR models) vary over the propensity scores. The results show that the ATT on both outcomes indicators varies significantly with the propensity score and that the slope is negative, suggesting that the effects of farmers based organization membership on land productivity and household income are stronger for households with the lowest probability to belong to a farmers organization and these effects decrease with the propensity of membership. The slopes coefficients of the graphs are estimated at 2.3 and 3.4 respectively for land productivity and household income. This would mean that with every 1 percentage point increase in the likelihood of membership in farmer organizations, the effect of membership on land productivity and household income would reduce respectively by 2.3% and 3.4%. The household income effect of membership in farmer organizations even becomes zero in the upper end of the propensity score distribution. These results to some extent are similar to those observed in Rwanda by Verhofstadt and Maertens (2015). As stated by these authors farmers who would take most from membership in producer organizations are the ones who face entry constraints (human or physical) and therefore are less keen to become members.

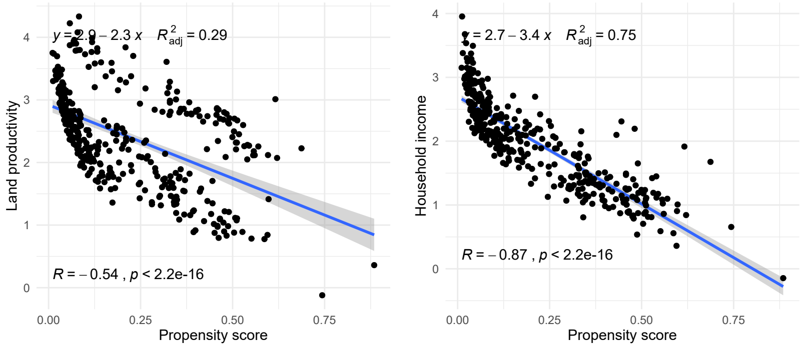

Figure 1: Heterogeneity over propensity scores

The OLS regression of the estimates of ATT, from the ESR models, on some of the characteristics of organization members are presented in table 8. Results show that the effect of membership in FBO on farm land productivity and household income appears to be different for each member. The impact of membership for both outcomes decreases significantly with the number of active persons living in the household and this effect is less important for those households who have access to extension services. Moreover, the effect has a U-shape relation with the age of the household head, implying that the effect of membership decreases with age for younger household heads and increases after a certain age. The impact of membership on land productivity also increases significantly with distance to the nearest road. Furthermore, this effect is less important for formally educated members. With regard to the household income, statistically significant differential effects are observed for other characteristics such as gender and the area of land possessed. The effect is larger for male members than for female members and it increases with the area of land possessed. OLS regressions results are at some extent corroborated by figures (3, 4, 5, 6 and 7) in the appendix. Moreover, membership effect appears to be determined by the specific type of organizations that households belong to. Results show that the impact of membership on land productivity is stronger for households who belong to the Economic Interest Groups. Meanwhile, the effect of membership on household income is more important for households who are members of Cooperatives. Furthermore, for both outcomes, this effect is less significant for households who are members of Rural Associations.

Table 8: Heterogeneous treatment effects:OLS regressions

	OLS without types of Farmer Organizations		OLS with types of Farmer Organizations	
	Land Productivity	Household Income	Land Productivity	Household Income
Intercept	3.714 (0.382)***	3.122 (0.256)***	3.847 (0.374)***	3.172 (0.251)***
Gender	0.021 (0.121)	0.202 (0.081)**	−0.039 (0.119)	0.181 (0.080)**
Age	−0.042 (0.014)***	−0.041 (0.009)***	−0.046 (0.014)***	−0.041 (0.009)***
Age Squared	0.001 (0.000)***	0.001 (0.000)***	0.001 (0.000)***	0.001 (0.000)***
Education	−0.476 (0.055)***	−0.060 (0.037)	−0.457 (0.054)***	−0.056 (0.036)
Active members	−0.040 (0.009)***	−0.060 (0.006)***	−0.037 (0.009)***	−0.059 (0.006)***
Migration	−0.101 (0.075)	0.060 (0.050)	−0.109 (0.073)	0.055 (0.049)
Equipment	−0.008 (0.065)	0.006 (0.044)	−0.026 (0.064)	0.008 (0.043)
Area owned	−0.008 (0.005)	0.038 (0.003)***	−0.007 (0.005)	0.036 (0.003)***
Distance to road	0.015 (0.002)***	0.000 (0.001)	0.014 (0.002)***	0.000 (0.001)
Extension	−0.901 (0.056)***	−1.074 (0.038)***	−0.944 (0.055)***	−1.098 (0.037)***
Types of Farmer Organizations				
Economic Interest Groups			0.181 (0.070)***	−0.032 (0.047)
Rural Associations			−0.208 (0.082)**	−0.162 (0.055)***
Producer Groups			−0.019 (0.084)	0.034 (0.057)
Cooperatives			0.125 (0.084)	0.157 (0.057)***
Adj. R^2	0.562	0.753	0.589	0.767
Num. obs.	372	372	372	372

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

5 Conclusion

In Senegal, recent renaissance of the cooperative movement coupled with the revival of the agricultural sector led us to explore the impact of farmer-based organization membership on cereals producing farm household land productivity and net incomes. Results were derived using a nationally represented household cross-sectional data collected in all agro-ecological regions and two econometric estimation techniques that control for selection bias arising from both observed and unobserved factors.

We find that the education of the household head, household size, distance to the nearest road, access to extension and to information on sales, living conditions of the household proxied by water source and the location of the household in various agro-ecological zones are the most important factors influencing households decision to belong to a producer organization. Additionally, findings suggest that membership in farmers' collective action groups is a key component of farm households' land productivity and income, and obtained results appear to be consistent throughout the two estimation methods. In particular, results from our preferred model, the Endogenous Switching Regressions, show that being a member of an organization helps to increase land productivity by almost twenty percent and household income by at least fourteen percent. Furthermore, membership in farmer organizations exhibits heterogeneous effects over the propensity score and over household characteristics. The estimated treatment effects are negatively correlated with households' likelihood to belong to a farmer-based organization, implying that the effect of membership is stronger for households with the lowest propensity to become members, meanwhile suggesting the possible existence of entry barriers that might face some farmers.

These results support once again the idea that farmer organizations have the potential to benefit farmers by increasing their incomes through the provision of conditions and the necessary social networks for access to technologies, knowledge, and production inputs. These collective action groups would, therefore, induce better farm productivity for improved incomes and then contribute to reducing rural poverty.

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Appendix

Table 9: Addressing potential endogeneity of extension variable

	Membership	Extension
Intercept	-1.809 (0.430)***	-1.850 (0.396)***
Gender	0.063 (0.125)	0.043 (0.111)
Age	0.027 (0.016)*	0.028 (0.014)**
Age Squared	-0.000 (0.000)**	-0.000 (0.000)*
Education	0.307 (0.060)***	0.255 (0.056)***
Active members	0.029 (0.010)***	-0.004 (0.010)
Dependents	0.024 (0.009)***	-0.007 (0.009)
Migration	0.067 (0.081)	0.272 (0.071)***
Equipment	0.002 (0.004)	0.003 (0.003)
Area owned	-0.002 (0.043)	0.080 (0.037)**
Distance to road	-0.007 (0.002)***	-0.006 (0.002)***
Groundnut AEZ	-0.917 (0.091)***	-0.656 (0.084)***
Casamance AEZ	-0.350 (0.094)***	-0.360 (0.090)***
South-East AEZ	-0.288 (0.111)***	-0.078 (0.103)
Information on Sales	0.842 (0.182)***	0.892 (0.176)***
Tap water	0.212 (0.071)***	0.083 (0.064)
Extension needs	-0.305 (0.359)	0.507 (0.238)**
Log Likelihood	-1152.478	-1371.070
Num. obs.	4245	4245

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 10: Propensity score matching quality test

	Before Matching	After Matching
Pseudo R2	0.177	0.005
LR χ^2	445.49	5.33
P-value ($p > \chi^2$)	0.000	0.997
Mean standardized bias	23.9	2.7

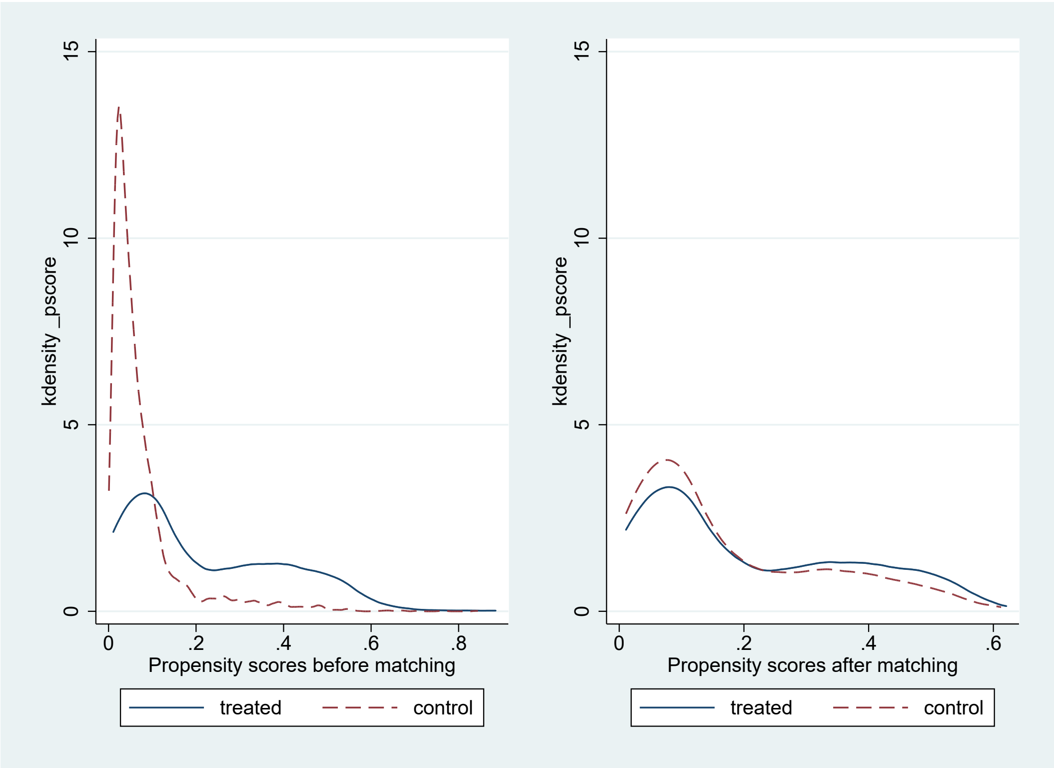

Figure 2: Kernel density of propensity scores

Table 11: Instrumental variable checking for ESR regressions

	Membership	Land Productivity		Household Income	
		Non-Members	Members	Non-Members	Members
Intercept	-1.87 (0.45)***	11.04 (0.21)***	12.88 (0.70)***	11.47 (0.26)***	12.27 (0.76)***
Gender	0.06 (0.13)	0.09 (0.06)	0.10 (0.22)	0.53 (0.07)***	0.77 (0.24)***
Age	0.02 (0.02)	-0.00 (0.01)	-0.03 (0.03)	0.00 (0.01)	-0.02 (0.03)
Age Squared	-0.00 (0.00)**	0.00 (0.00)	0.00 (0.00)	-0.00 (0.00)	0.00 (0.00)
Education	0.31 (0.08)***	0.12 (0.03)***	-0.12 (0.10)	-0.02 (0.04)	0.04 (0.11)
Active members	0.03 (0.01)***	0.02 (0.01)***	0.03 (0.02)	0.06 (0.01)***	0.05 (0.02)**
Dependents	0.03 (0.01)***	-0.00 (0.01)	-0.01 (0.02)	0.02 (0.01)***	-0.00 (0.02)
Migration	0.04 (0.10)	-0.06 (0.04)	-0.16 (0.14)	-0.10 (0.05)*	-0.14 (0.15)
Equipment	-0.01 (0.05)	0.08 (0.03)***	0.16 (0.12)	0.13 (0.03)***	0.29 (0.13)**
Area owned	0.00 (0.00)	-0.01 (0.00)***	-0.02 (0.01)*	0.04 (0.00)***	0.05 (0.01)***
Distance to road	-0.01 (0.00)***	-0.00 (0.00)***	-0.01 (0.00)	-0.01 (0.00)***	-0.01 (0.00)**
Extension	0.29 (0.83)	0.27 (0.06)***	0.36 (0.10)***	0.27 (0.07)***	0.14 (0.11)
Groundnut AEZ	-0.89 (0.15)***	-0.24 (0.05)***	-1.23 (0.17)***	0.00 (0.06)	0.03 (0.19)
Casamance AEZ	-0.32 (0.12)***	0.36 (0.06)***	-0.82 (0.17)***	0.12 (0.07)*	-0.14 (0.18)
South-East AEZ	-0.28 (0.12)**	0.35 (0.07)***	-1.10 (0.19)***	0.24 (0.08)***	-0.02 (0.20)
Information on Sales	0.80 (0.29)***	0.09 (0.16)	0.15 (0.23)	0.26 (0.19)	0.53 (0.25)**
Tap water	0.20 (0.08)***	-0.00 (0.04)	0.23 (0.12)*	-0.02 (0.04)	0.16 (0.13)
Extension residuals	0.44 (0.44)				
Adj. R^2		0.10	0.29	0.15	0.25
Log Likelihood	-1038.13				
Num. obs.	4245	3873	372	3873	372

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

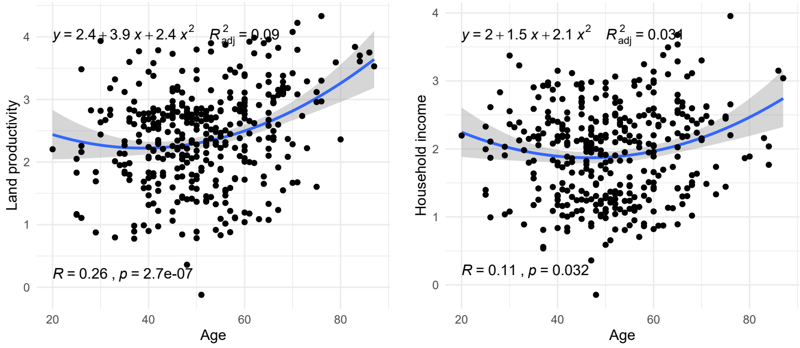

Figure 3: Heterogeneity over household head age

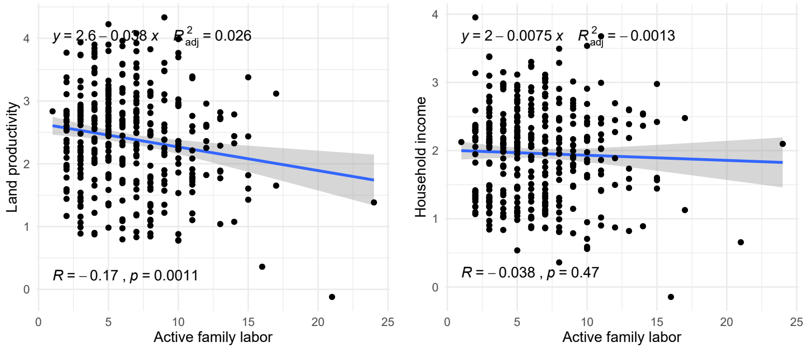

Figure 4: Heterogeneity over active family labour

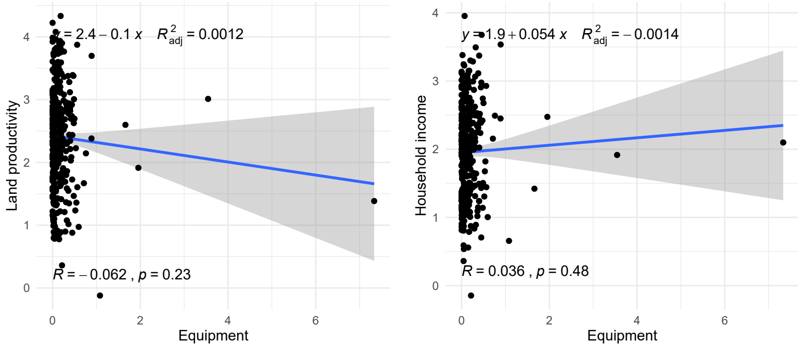

Figure 5: Heterogeneity over agricultural equipment ownership

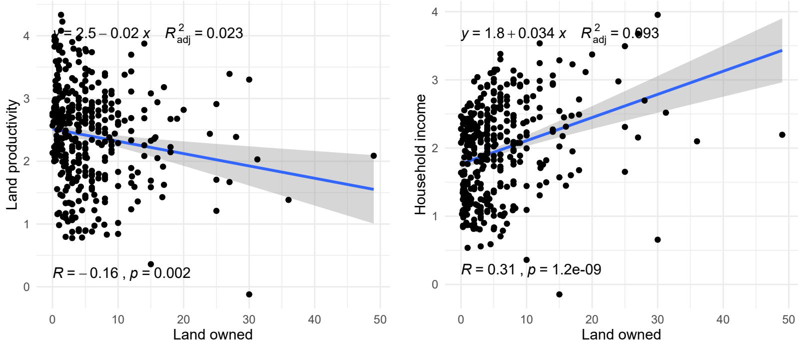

Figure 6: Heterogeneity over land ownership

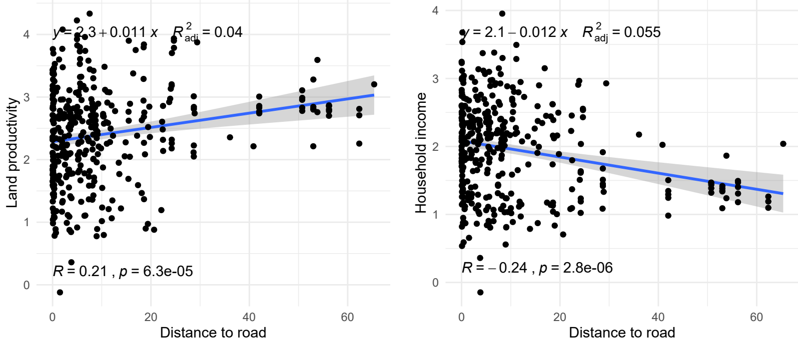

Figure 7: Heterogeneity over access to road