A stochastic meta-frontier approach to estimating the impact of cooperatives membership on rice farmers' efficiency: Contrasting results from Senegal

K. Christophe Adjin* and Christian H. C. A. Henning

Institute of Agricultural Economics, University of Kiel (Germany)

Contributed Paper prepared for presentation at the 94th Annual Conference of the Agricultural Economics Society, KULeuven, Belgium

15 - 17 April 2020

*Corresponding author, Wilhelm-Seelig-Platz 7, 24118 Kiel. cadjin@ae.uni-kiel.de

Abstract

Using cross-sectional data from 835 rice-farming households in Senegal, we investigated the extent to which membership in farmers' cooperatives affects farm technical efficiency. To do so, we combine the propensity score matching method with the sample selection stochastic frontier model (Greene, 2010) and the stochastic meta-frontier approach (Huang et *al*., 2014). The propensity score matching helps in mitigating biases from observable variables. The sample selection stochastic frontier framework was used to control for biases arising from unobserved characteristics in the production frontier. Using the meta-frontier approach, farmers' technical efficiency were estimated and compared. Results show that cooperative membership contributes significantly in improving rice production. However, when considering group-specific frontiers (farmers operating in their own benchmark: members vs non-members), cooperatives members do not technically perform better than non-members. Furthermore, when considering the meta-frontier estimates, significant differences in technical efficiency between members and non-members can still be observed in favour of non-members.

Keywords: Agricultural cooperatives, Farm technical efficiency.

JEL code: Agricultural cooperatives Q130, Efficiency D240.

1 Introduction

According to FAO statistics (FAO, 2019), rice in sub-Saharan Africa, is the most important cereal in terms of production. Rice has become an economically important crop and the main staple food of millions of people. Indeed, due to population growth (4% per year) and a shift in consumption habits in favor of rice, the relative growth of demand for rice is faster in sub-Saharan Africa than anywhere else in the world (Balasubramanian *et al.*, 2007; Seck *et al.*, 2010).

In Senegal, rice occupies an important position nationally both in terms of consumption and production. Average annual consumption over the last decade (2007–2016) was more than 1.2 million [1] of tonnes of milled rice while the average yearly production over the same period was only 358,357 tonnes [2]. There is, therefore, a significant gap between production and consumption, which is filled with large-scale rice importation every year. Milled rice imports have increased from 536,870 tonnes in 2000 to more than 973,000 tonnes in 2016, at an average annual cost of about 315 million US dollars (FAO, 2019).

This gap between domestic production and consumption denotes a real food security problem in Senegal. The country was hardly hit by the 2007–2008 food crisis, with violent riots observed during the crisis (Seck *et al.*, 2010; Diagne *et al.*, 2013). Besides, the heavy dependence on imports represents a serious burden on the country's trade and foreign exchange balance. Reducing Senegal's dependence on imported rice and meeting the population's demand for rice are real challenges for the Senegalese government. Hence, since 2009, priority has been given by the government to the domestic rice sector because of its potential to provide national food security, support economic growth and alleviate poverty (République du Sénégal, 2009). The 2014-2017 revised National Program for Self-Sufficiency in Rice ("Programme National d'Autosuffisance en riz - PNAR") intended to increase rice production in the country to reach self-sufficiency in 2017[3].

To achieve this goal and for the rice sector to express its full potential, rice farmers need to have access to production inputs and technologies, which constitute, however, general challenging factors for the agricultural sector in most developing countries (World Bank, 2007). According to Salifu *et al.* (2010), to overcome these challenges and improve agricultural performance, policymakers regarded during decades, collective action groups, such as cooperatives, as a high instrumental tool. Nowadays, this agricultural development approach based on farmers' groups or cooperatives, prevails. However, such an approach is increasingly supported by quantitative studies in which scholars try to evaluate the effective contribution of agricultural cooperatives membership to various agricultural indicators.

Therefore, during the last decade, an important body of literature was dedicated

[1] Consumption here refers to apparent consumption and it is computed using data collected from the FAOSTAT website. Consumption equals to paddy rice produced converted into milled rice using a ratio of 0.67 plus imports and net of export

[2] Statistics compiled using paddy rice production data of FAOSTAT website (FAO, 2019), using a paddy to milled rice conversion factor of 0.67 (ref.)

[3] http://sakss.sn/programme-national-dautosuffisance-en-riz-pnar

to the analyses of the impact of cooperatives on farmers welfare (Fischer and Qaim, 2012b; Mojo *et al.*, 2017; Ahmed and Mesfin, 2017; Verhofstadt and Maertens, 2015; Ito *et al.*, 2012; Ma and Abdulai, 2016; Mishra *et al.*, 2018), Commercialization and marketing (Wollni and Zeller, 2007; Bernard *et al.*, 2008; Bernard and Spielman, 2009; Barham and Chitemi, 2009; Bernard and Spielman, 2009; Francesconi and Heerink, 2010; Chagwiza *et al.*, 2016; Fischer and Qaim, 2012b), technology adoption (Abebaw and Haile, 2013; Ma *et al.*, 2018a). However, regarding the association between cooperatives membership and farm productivity and efficiency, very few researches have been done, especially concerning technical efficiency analysis.

A review of studies shows that cooperatives' membership has a positive impact on farmers' yields and productivity (Ma *et al.*, 2018a; Mishra *et al.*, 2018; Francesconi and Ruben, 2012). Concerning the impact of membership on technical efficiency, the causal relationship between cooperatives and technical efficiency is not straightforward and not conclusive. Abate *et al.* (2014) showed that cooperatives through the mechanism of easing access to productive inputs contribute significantly to members' technical efficiency. Contrarily, in Ghana, Addai *et al.* (2014) study indicated no significant impact of maize farmers' groups' membership on technical efficiency.

These two authors used a combination of a matching approach and a frontier approach with the assumption of similar technology for members and non-members. However, this assumption generally cannot hold. Mostly farmers join cooperatives to have access to improved technologies and to increase their productivity and technical efficiency. The membership to a cooperative becomes then endogenous. Therefore, it is crucial to take into account biases that arise from endogenous self-selection and technological heterogeneity. These potential biases were then considered in the two recent papers of Abdul-Rahaman and Abdulai (2018) and Ma *et al.* (2018b). Where they used a propensity score matching approach and the sample-selection stochastic frontier approach (Greene, 2010) to control for selection biases in the production frontiers. They then designed two groups frontiers (members and non-members) and compared farmers' technical efficiencies from their respective group's frontiers. By doing so, these authors found that cooperatives members are more technically efficient than non-members. However, the two groups of farmers are operating against two different benchmarks, comparing their technical efficiency estimates does not permit to estimate the real difference in the productivity of the two groups of farmers (Villano *et al.*, 2015; Henningsen *et al.*, 2015). In addition to the groups' frontiers, a meta-frontier approach to evaluate the technical efficiency of farmers would have been a more robust approach to compare farmers' technical efficiencies.

This paper has the objective to investigate the causal relation between cooperatives membership and farm efficiency in Senegal, by using a methodology that combines three different approaches. First, to correct the selection bias, we used a propensity score matching approach. Secondly, to take into account both technology heterogeneity and cooperatives membership when comparing the efficiency between members and non-members, we use Greene (2010) sample selection frontier to estimate two separated stochastic production frontiers. Finally, following Huang *et al.* (2014) we built a stochastic meta-frontier that works as a benchmark against which the performances of different farms could be compared to. The remainder of this paper is organized as follows. The next section describes the suggested econometric framework. he third section presents the used data. The following section presents the estimation results and their discussion. In the final section, results are summarized with some policy recommendations.

2 Econometric Framework

The main objective of this paper is to investigate the effect that cooperatives' membership has on farmers' technical efficiency. To do so, we adopted an econometric framework that combines three main approaches. To address the issue of selection bias arising from observables, we used the propensity matching approach. The Greene (2010) sample selection stochastic frontier model helped us to address the selection bias resulting from unobservables in the designed frontiers. To take into account the technology heterogeneity that could result from cooperatives' membership, we used Huang *et al.* (2014)'s meta-frontier approach to derive the technology gap and to compare efficiencies between members and non-members.

2.1 Modeling Cooperatives membership

Cooperatives membership can be modeled within the random utility framework. In this framework, a household chooses to a member of a cooperative if the expected utility gained from cooperative membership (M_{i1}) is larger than the one from non-membership (M_{i0}). This means that a household is a member of a cooperative if the expected net utility ($M_{i1} - M_{i0}$) is greater than zero. This utility gain can be specified as a function of observed covariates (Z) in a latent variable model as follows:

$$M_i^* = \alpha^{'} z_i + w_i, \;\; M_i = 1 \text{ if } M_i^* > 0, \tag{1}$$

where M_i is a binary variable that takes the value 1 for a household i member of cooperatives and 0 otherwise; α is a vector of parameters to be estimated; z_i is a vector of exogenous farm and household characteristics, and w_i is an error term. For many researchers, participating in an agricultural cooperative increases the adoption level of new agricultural technologies, through various mechanisms (see e.g. (Fischer and Qaim, 2012b,a; Abebaw and Haile, 2013). Then, the frontier production function might differ between cooperatives members and non-members due to technology accessibility and adoption. It becomes therefore intuitive to design two different production functions for cooperatives members and non-members, and statistically compare and test their parameters. However, proceeding so is complicated because of the self-selection in cooperatives membership and the following choice of technology ((Mayen *et al.*, 2010).

2.2 Stochastic Frontier Approach

We adopt the stochastic frontier analysis (SFA) framework to estimate the production frontiers and measure the technical efficiency of farmers. The standard stochastic production frontier model is specified as:

$$y_i = f(x_i, \beta) \exp(v_i - u_i), \tag{2}$$

where y_i denotes the output for the i^{th} farm ($i = 1, ..., N$), x_i is a vector of inputs, β are parameters to be estimated, v_i is a two-sided stochastic term that accounts for statistical noise, u_i is a non-negative stochastic term representing inefficiency, and ε_i is the composite error term ($\varepsilon_i = v_i - u_i$). Generally, it is assumed that v_i and u_i are identically and independently distributed, u_i follows a half-normal distribution with variance σ_u^2 and v_i follows a normal distribution with variance σ_v^2. This model is usually estimated using the maximum likelihood estimator as suggested by Aigner *et al.* (1977). After the estimation of the frontier model, following Jondrow *et al.* (1982) (JLMS thereafter) one can calculate the farm-specific technical efficiency.

2.3 Correcting for selection bias

Following Ma *et al.* (2018b); Abdul-Rahaman and Abdulai (2018), we first use the Propensity Score Matching method to match members with non-members in the sample. Then we use the sample selection frontier approach to correct for selectivity bias in the production frontier.

2.3.1 Propensity Score Matching (PSM)

PSM uses observable characteristics of units in the sample to generate a control group that is as similar to the treated group as possible except for treatment status, here the cooperative membership (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 cooperatives membership decision is only based on observable characteristics of households. The second is the common support or overlap condition that needs to be satisfied, i.e. the distributions of observable characteristics between members of cooperatives (the treated) and non-members (the untreated) have to overlay (Jelliffe *et al.*, 2018).

2.3.2 Sample Selection Stochastic Production Approach

Sample selection bias arises when there is a correlation of the unobservables in the production function equation with those in the sample selection equation. In recent years, the literature reveals two main alternative applications of the sample selection modeling in the stochastic frontier model. Kumbhakar *et al.* (2009) suggested a model framework in which the selection mechanism operates through the one-sided error (u_i). Greene (2010) proposed a framework where the selection mechanism is operated through the error term v_i. The first model requires computationally demanding log-likelihood functions ((Villano *et al.*, 2015). Therefore, in this paper, we follow Greene (2010) approach, designing for farmers two simultaneous equations: a selection equation and a production function equation. The specification of this model is derived as follows:

$$\text{Selection equation} : M_i = 1\left[\alpha' z_i + w_i > 0\right],\ w_i \sim N\left[0,1\right]$$

$$\begin{aligned} \text{SFP function} : y_i &= f(x_i,\beta) + \varepsilon_i,\ \varepsilon_i \sim\ N\left[0,\sigma_\varepsilon^2\right] \\ &(y_i, x_i) \text{ observed only when } M_i = 1. \end{aligned} \tag{3}$$

$$\begin{aligned} \text{Error structure} : \varepsilon_i &= v_i - u_i \\ u_i &= |\sigma_u U_i| = \sigma_u |U_i| \text{ where } U_i \sim N\left[0,1\right] \\ v_i &= \sigma_v V_i \text{ where } V_i \sim N\left[0,1\right] \\ (w_i, v_i) &\sim N_2\left[(0,1),(1,\rho\sigma_v,\sigma_v^2)\right], \end{aligned}$$

where M_i is a dummy variable of farmers $i(i = 1,..,N))$, that takes the value of 1 for cooperatives members and 0 for non-members, z_i is a vector of covariates in the sample selection equation, w_i is the error term of the selection equation, and y_i, x_i, v_i, u_i and ε_i are defined as previously. The inefficiency term u_i is assumed to follow a half-normal distribution with variance σ_u^2 and w_i and v_i are assumed to follow a bivariate normal distribution with variances 1 and σ_v^2, respectively, and a correlation coefficient of ρ. Parameters ρ, α and β are to be estimated. Non-zero values of ρ indicate the presence of selection bias and when $\rho = 0$, the model reduces to that of the standard stochastic frontier model.

Following Greene (2010), a two-step estimation procedure is used. In the first step we modeled membership into cooperatives with the selection equation (Eq.1), using a probit model. Consistent ML estimates of α are obtained and used to derive the conditional simulated log likelihood function of the combination of equations 1 and 3 (for more details, see Greene (2010)).

Empirically, for the selection model, the variable M_i is a dummy representing the likelihood that the farmer belongs to a cooperative, taking the value of 1 if the farmer is a member of cooperative and 0 otherwise, z is defined as previously. Similarly to Bravo-Ureta *et al.* (2012) and Abdul-Rahaman and Abdulai (2018), we estimated two stochastic frontier models, one for cooperatives members and one for non-members. Once the two stochastic frontier models are estimated, one can derive the group-specific technical efficiency estimates both for cooperatives members and non-members. To do so, we used the JLMS approach and then compared these efficiency scores against each benchmark.

However, our methodological framework still has one limitation. It is not possible to compare directly the estimated farms' individual technical efficiency between cooperatives members and non-members since these scores pertain to each group's own frontier (González-Flores *et al.*, 2014; Villano *et al.*, 2015; Henningsen *et al.*, 2015). Therefore, in order to address this issue, we used a meta-frontier approach that enables us to estimate and compare the technical efficiency of production units regrouped in different types of technology.

2.4 Meta-Frontier approach

Considering that all farmers are gathered in J groups ($j = 1, 2$) and farmers in each group operate under a group-specific technology, with group-specific frontiers defined as $f^j(x_{ji})$ and $f(.)$ a specified functional form. Commonly, the meta-frontier production function $f^M(x_{ji})$ that envelops all different groups' frontiers $f^j(x_{ji})$ is expressed as:

$$f^j(x_{ji}) = f^M(x_{ji}) \exp(-u_{ji}^M), \ \forall \ j, i, \tag{4}$$

where$u_{ji}^M \geq 0$, therefore $f^M(.) \geq f^j(.)$ and the relationship of the j^{th} production frontier to the meta-frontier is defined as the meta technology ratio (MGR), which expresses the difference in efficiency due to the choice of a particular technology, and it is between zero and one. To estimate the metafrontier, we follow Huang *et al.* (2014) approach that has the main advantage to allow statistical interpretations. In the first step, the standard maximum likelihood (ML) estimation is used to estimate group-specific frontiers. In a second step, a stochastic frontier model (as in equation 5) is formulated and estimated by the maximum likelihood to obtain the estimates of the meta-frontier:

$$\hat{f}^j(x_{ji}) = f^M(x_{ji}) \exp(v_{ji}^M - u_{ji}^M), \ \forall i, j = 1, 2. \tag{5}$$

This equation is similar to the traditional stochastic frontier, where $\hat{f}^j(x_{ji})$ represents the estimates of the group-specific frontier, u_{ji}^M ($u_{ji}^M \geq 0$) is the technological gap and is assumed to follow a truncated-normal distribution with the mode μ^M and independent from v_{ji}^M, and v_{ji}^M is assumed to follow a normal distribution with zero mean, but non independently and identically distributed. Additionally, the mode $\mu^M(q_{ji})$ is a function of environmental variables q_{ji}.

As described by Huang *et al.* (2014), for each level of inputs, an associated output level y_{ji} with respect to the meta-frontier $f^M(x_{ji})$ has three components: the meta technology ratio $MTR_i^j = \frac{f^j(x_{ji})}{f^M(x_{ji})}$, the group specific technical efficiency of each production unit $TE_i^j = \frac{y_{ji}}{f^j(x_{ji}) \exp(v_{ji})} = \exp(-u_{ji})$, and the technical efficiency of each farmer regarding the meta-frontier $MTE_i^j = \frac{y_{ji}}{f^M(x_{ji}) \times \exp(v_{ji})} = MTR_i^j \times TE_i^j$.

2.5 Empirical Strategy

As stated previously, to correct for selectivity bias, we use first the propensity score matching method and then a sample selection stochastic frontier approach. Following Ma *et al.* (2018b); Abdul-Rahaman and Abdulai (2018) in a first step, we generated the propensity score of belonging to a cooperative, using a probit model, by regressing the cooperative membership variables on farm observable characteristics (see table 1). In the PSM approach, numerous algorithms can be applied to match members and non-members of similar propensity scores. We use the most common matching technique: the nearest neighbor matching with five neighbors and caliper of 0.01. By doing so, a total of 787 matched farmers are obtained including 105 members of cooperatives and 682 non-members with a similar range of observable characteristics. Table A1 in the appendix presents the propensity score of cooperative membership for the matched and unmatched samples. The balancing test results are also presented in table A2. From table A2 significant differences can be observed between members and non-members in most of the variables in the unmatched sample. Contrarily, no significant differences in the observed characteristics could be found in the matched sample, suggesting that balancing condition is satisfied (Caliendo and Kopeinig, 2008). In addition, the common support condition is also satisfied, as shown in figure 1.

Once the matched sample obtained, we estimated the sample-selection stochastic frontier model. Here, the first stage is the estimation of the selection equation (eq. 1) as a standard probit model. Several factors are associated with cooperatives membership ((Fischer and Qaim, 2012b; Abebaw and Haile, 2013; Tolno *et al.*, 2015; Mojo *et al.*, 2017)), including personal details of household head (gender, age, education level) and household characteristics (e.g. household size, agricultural assets, land size), the access to rural various institutions (e.g. agricultural extension services, credits), the geographic location of the household. Based on previous studies, in our empirical specification, we assume that the probability that a household belongs to a cooperative member is a function of these main selected variables. However, it is worth noting that households could have better access to extension due to cooperative membership, rendering the access to extension services variable potentially endogenous in the modeling of cooperative membership, and leading then to biased estimates. We, therefore, corrected this endogeneity issue with the two-stage control function approach suggested by Wooldridge (2015)[4]. The variables used to model the cooperative membership are presented in table 1.

The second stage of the sample selection stochastic frontier model is the estimation of the production function. To do so, from preliminary comparisons using the pooled unmatched data, a maximum likelihood ratio test led to the rejection of the Cobb-Douglas (CD) in favor of the translog (TL) functional form ($\chi^2 = 79.28, p < 0.01$), which has the main advantage to add the effects of interactions between inputs. Also, the Akaike Information Criterion of the translog ($AIC = 2099.47$) was less than that of the Cobb Douglas ($AIC = 2158.75$). Therefore, we used translog specification or all analyses and it is expressed as:

$$y_i = f(x_i, \beta) + \delta D_i + \gamma G_i + \varepsilon_i, \ \varepsilon_i \sim \ N\left[0, \sigma_\varepsilon^2\right], \tag{6}$$

where y_i represents the natural logarithm of the output of the i^{th} farmer, x_{ik}, x_{il}

[4]In a first stage, we estimated separately, the access to extension services and the cooperative membership on the same independent variables plus an instrument (here the number of plots owned by the farmer) using a probit model. The instrument, the number of plots owned by the household, significantly influences the access to extension services but not directly influences the household membership to cooperatives (see table A3 in the appendix). In the second-stage probit estimation, the access to extension services variables and their generalized residuals predicted from the first-stage are included in the cooperative membership equation and estimated

denote vectors of the natural logarithm of production inputs k or l, for $k \neq l$; D represent dummy variables; G represent other contextual variables; β, δ and γ are parameters to be estimated; ε_i is the composite error term as defined previously and comprising v_i and u_i.

The output here is the total rice production (in kilograms). The four inputs included in the models are the land cultivated (in hectare), the quantity of seeds (in kilograms), the quantity of total labor (in equivalent working-days) and the quantity of fertilizers (in kilograms). The dummy variables are cooperative membership, the use of certified seeds and the non-use of fertilizers. The other environmental variables are the percentages of clay and silt elements in soils, and the rainfall of the survey year 2017 (in millimeters)[5]. We follow Battese (1997) approach, to account for zero values of fertilizer use by including a dummy for the non-use of fertilizer, such that the logarithm of the fertilizer with zero values is taken only if it is positive, and zero otherwise.

To identify whether it is necessary to estimate separate frontiers for members and non-members, we first estimated a pooled stochastic production frontier including a dummy variable for cooperative membership. Then, two separate stochastic production frontier models for members and non-members are estimated. Finally, using a likelihood ratio test, we checked if there is a difference in technologies used by the two groups of farmers (Bravo-Ureta *et al.*, 2012). Specifically, the estimated likelihood ratio (LR) can be estimated as follows:

$$LR = -2 \times (\ln Lp - (\ln L1 + \ln L0)), \tag{7}$$

where $\ln Lp$, $\ln L1$ and $\ln L0$ respectively denote the log-likelihood values for the pooled stochastic production frontier model, the cooperative members' sample, and the non-members'. Where the null hypothesis is that members and non-members use the same rice production technology. For the estimation of the meta-frontier, the second step environmental variables or sector-specific variables (that are supposed to impact the group-specific technology gap ratio) included in the four meta-frontier models are the agro-ecological zones of Casamance and the Delta, and three environmental risks such as the presence of grains bird [6], drought and the early stop of rain. The estimations of the conventional stochastic production frontier for both matched and unmatched samples were performed using the R software, while the PSM was conducted in STATA software and NLOGIT 6 was used to estimate the sample selection stochastic production frontier models.

[5]Rainfall and soil percentages of clay, silt and sand were retrieved from publicly available database from International Soil Reference and Information Centre (ISRIC – World Soil Information) at https://data.isric.org/ using the geographical coordinates of each household. The Database uses machine learning and data collected in 2017 and 2018

[6]According to (de Mey *et al.*, 2012), annual bird damage in average can exceed more than 13% of the potential rice production during wet seasons.

3 Data Sources and Descriptive Statistics

3.1 Data Sources

The data used derived from a survey conducted in Senegal, which randomly sampled 4533 households that mainly produce dry cereals (rainfed cereals). Data was collected in 2017 in the framework of the Agricultural Policy Support Project funded by USAID. Senegalese National Agricultural Research Institute conducted the survey, with the support of the International Food Research Institute (IFPRI). A multi-stage 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 crop productions, cooperative membership, household assets, access to infrastructure, access to institutions, and household demographic and socioeconomic characteristics. Besides crops' productions and the used inputs information, data collection also included market prices and households adoption of agricultural technologies (certified seed and fertilizers) during the main agricultural season of 2016. After the data cleaning process, we retrieved the set of 835 farmers that produced rice during the 2016 season.

3.2 Variables Descriptive Statistics

Table 1 presents the definition and summary statistics of the variables used in the analysis. The households in the sample are predominantly male-headed, i.e. 90%. The household heads are generally aged with an average of 53 years and without any formal education, (53%). The households' heads are mainly farmers, however, the households also get revenues from off-farm activities (41%). On average, the household includes more than nine family members and owns about 3.55 hectares of agricultural land. About 18% of these households are members of cooperatives.

Regarding the production variables, the farmers produce on average 1407 kg of rice. However, the standard deviation shows that there is a huge variation in the production output. To produce rice, farmers dedicate an average of 0.9 hectares, 52 kg of seeds and 86 kg of fertilizers. However, most of the farmers do not use fertilizers (61.8%). In addition, around 3 equivalent persons work on rice plots during the season. all outcomes are log specified. Concerning the matching variables, following the literature we included several variables e.g. the household and its heads characteristics, the household's assets (agricultural implements index) [7], the geographical location, the household access to rural institutions, the agro-ecological zones.

[7]Following the standard approach for calculating a welfare index, we have computed the agricultural implements index by using dummy variables of the possession of 17 agricultural assets such as donkey carts, horse cart, cattle cart, tractor, sine hoes, plows, occidental hoes, sheller, polyculture, arenas, thresher, harvester, sprayer, sower, storage, hangar, atomizer

Table 1: Description of variables

Variables	Description and measurement	Type	Mean (SD)
Cooperative	Membership status in a cooperative (1=yes, 0=no)	Dummy	0.183 (0.387)
	Household and Head characteristics		
Sex	Gender of household head (1=yes, 0=no)	Dummy	0.897 (0.304)
Age	Age of household head (years)	Continuous	53.589 (12.726)
Household size	Number of family members	Continuous	9.647 (5.200)
Off-farm	Household involved Off-farm work (1=yes, 0=no)	Dummy	0.412 (0.492)
No education	No formal education (1=yes, 0=no)	Dummy	0.534 (0.499)
	Assets & living conditions		
Land owned	Total land size owned by the household (hectares)	Continuous	3.553 (5.750)
Implements index	Agricultural implements index	Continuous	-1.004 (0.834)
Number of plots	Number of plots owned	Continuous	2.838 (1.652)
	Location		
Distance to road	Distance to the nearest all-weather road (km)	Continuous	11.140 (12.904)
Distance to market	Distance to the nearest main market (km)	Continuous	15.964 (12.802)
	Access to institutions		
Extension	Access to extension services (1=yes, 0=no)	Dummy	0.198 (0.398)
Credit	Access to credit (1=yes, 0=no)	Dummy	0.019 (0.137)
Certified seed	Adoption of certified seed (1=yes, 0=no)	Dummy	0.210 (0.407)
	Ecological conditions		
Casamance AEZ	Casamance agro-ecological zone (1=yes, 0=no)	Dummy	0.759 (0.428)
Delta AEZ	Delta agro-ecological zone (1=yes, 0=no)	Dummy	0.097 (0.296)
Rainfall	Rainfall 2016 (mm)	Continuous	1046.283 (386.948)
Clay	Percentage of clay (%)	Continuous	27.594 (4.090)
Silt	Percentage of silt (%)	Continuous	17.844 (3.286)
Granivorous Birds	Granivorous birds damage (1=yes, 0=no)	Dummy	0.192 (0.394)
Drought	Drought (1=yes, 0=no)	Dummy	0.062 (0.242)
Early Rain Stop	Early rain stop (1=yes, 0=no)	Dummy	0.325 (0.468)
	Production inputs		
Land	Total area cultivated (hectares)	Continuous	0.900 (1.100)
Labor	Total labor size (equiv. work-days.)	Continuous	232.123 (258.244)
Seeds	Total seeds (KG)	Continuous	52.070 (62.930)
Fertilizers	Total fertilizers (KG)	Continuous	86.540 (390.630)
No Fertilizers	Non use of fertilizers (1=yes, 0=no)	Dummy	0.618 (0.486)
	Outcome variable		
Rice Production	Total crops productions (KG)	Continuous	1407.10 (5742.24)
N	Number of Observations		835

3.3 Comparative Descriptive Statistics

Table 2 shows the comparative descriptive statistics of the characteristics of cooperative members and non-members for the matched and unmatched samples. Significant differences are observed between members and non-members mostly with the unmatched sample. Cooperative members tend to have larger households (10 persons) than non-members(9 persons). They are also less involved in off-farm works and possess fewer agricultural implements. Cooperatives members have better access to rural institutions (extension, credit and certified seeds) relatively to nonmembers. Furthermore, they use more agricultural production inputs (land, labor, seeds, and fertilizers) and produce much more quantities of rice compared to non-members.

Table 2: Comparative Descriptive Statistics

	Unmatched Sample			Matched Sample		
Variables	**Members**	**Non-Members**	**P-value**	**Members**	**Non-Members**	**P-value**
Sex	0.93 (0.26)	0.89 (0.31)	0.12	0.91 (0.28)	0.89 (0.31)	0.42
Age	52.58 (12.32)	53.82 (12.81)	0.27	51.83 (12.51)	53.82 (12.81)	0.13
Household size	10.33 (5.05)	9.49 (5.22)	0.07	10.78 (5.57)	9.49 (5.22)	0.03
Off-farm	0.28 (0.45)	0.44 (0.50)	<0.01	0.34 (0.48)	0.44 (0.50)	0.05
No education	0.58 (0.49)	0.52 (0.50)	0.19	0.52 (0.50)	0.52 (0.50)	0.99
Land owned	3.00 (4.89)	3.68 (5.92)	0.14	3.12 (3.39)	3.68 (5.92)	0.16
Implements index	-1.16 (1.00)	-0.97 (0.79)	0.03	-1.02 (1.00)	-0.97 (0.79)	0.60
Number of plots	2.57 (2.01)	2.90 (1.56)	0.06	2.77 (1.95)	2.90 (1.56)	0.52
Distance to road	17.16 (17.66)	9.79 (11.15)	<0.01	13.86 (15.56)	9.79 (11.15)	0.01
Distance to market	17.09 (15.15)	15.71 (12.21)	0.30	15.46 (14.24)	15.71 (12.21)	0.87
Casamance AEZ	0.41 (0.49)	0.84 (0.37)	<0.01	0.44 (0.50)	0.84 (0.37)	<0.01
Delta AEZ	0.41 (0.49)	0.03 (0.16)	<0.01	0.03 (0.17)	0.03 (0.16)	0.28
Extension	0.61 (0.49)	0.10 (0.31)	<0.01	0.44 (0.50)	0.10 (0.31)	<0.01
Credit	0.06 (0.24)	0.01 (0.10)	0.01	0.57 (0.50)	0.01 (0.10)	<0.01
Certified seed	0.56 (0.50)	0.13 (0.34)	<0.01	0.23 (0.42)	0.13 (0.34)	<0.01
Rainfall 2016	673.73 (535.05)	1129.86 (285.12)	<0.01	856.02 (520.90)	1129.86 (285.12)	<0.01
Clay (%)	26.49 (4.75)	27.84 (3.89)	<0.01	26.40 (5.01)	27.84 (3.89)	0.01
Silt (%)	16.69 (4.16)	18.10 (3.00)	<0.01	16.58 (4.29)	18.10 (3.00)	<0.01
Granivorous Birds	0.43 (0.49)	0.14 (0.34)	<0.01	0.34 (0.48)	0.14 (0.34)	<0.01
Drought	0.07 (0.25)	0.06 (0.24)	0.86	0.10 (0.29)	0.06 (0.24)	0.27
Early Rain Stop	0.17 (0.38)	0.36 (0.48)	<0.01	0.22 (0.42)	0.36 (0.48)	<0.01
Land	1.09 (1.93)	0.86 (0.80)	0.15	1.15 (2.23)	0.86 (0.80)	0.18
Labor	244.40 (203.18)	229.37 (269.11)	0.44	223.95 (200.54)	229.37 (269.10)	0.81
Seeds	70.50 (96.08)	47.93 (51.98)	0.01	61.82 (88.18)	47.93 (51.98)	0.12
Fertilizers	278.16 (832.28)	41.41 (138.05)	<0.01	265.56 (977.00)	41.41 (138.05)	0.02
No Fertilizers	0.27 (0.45)	0.70 (0.46)	<0.01	0.39 (0.49)	0.70 (0.46)	<0.01
Rice Production	4153.39 (12950.56)	790.71 (959.23)	<0.01	4040.12 (15031.26)	790.71 (959.23)	0.03
N	153	682	835	105	682	817

4 Results and Discussion

4.1 Determinants of Cooperatives Membership

Factors that determine households' decision to belong to a cooperative are presented in table 3 with their marginal effects. The likelihood ratio test shows that the model estimates are significant at 1% level ($\chi^2(14) = 265.58$; $p < 0.01$). Table3 also shows the residual coefficient from the first-stage of the access to extension services variable which is a potential endogenous variable. The results show that the residuals are not statistically significant, suggesting that the access to extension services is not endogenously correlated to the household's decision to belong to a cooperative.

The results of the estimation of equation (1) suggest that the main factors that have a significant influence on whether the farmer decides to be a member of a cooperative are the household size, the access to extension services and to credit. The household size has a positive and significant effect on cooperative membership. These results support those of Bernard and Spielman (2009) and Ma and Abdulai

(2016). Those households who have more members have higher probability (0.8%) to be a member of cooperatives. With more members, these households have a better chance that one of their members could belong to a cooperative. Variables such as access to extension services and credit affect positively and significantly the farmers' probability to be members of cooperatives. Farmers who have access to extension services are about 58.6% more likely to join cooperative and those that have access to credit have 25.7% to be members. The access to various institutions e.g. agricultural extension services (Abebaw and Haile, 2013) and credits (Abdul-Rahaman and Abdulai, 2018) and even to cooperatives Mojo *et al.* (2017) is, in the previous literature, associated with cooperatives' membership.

Table 3: Probit Estimates of Cooperative Membership: Unmatched Sample

	Coefficients	Marginal Effects
Intercept	-1.134 $(0.471)^{**}$	
Sex	0.057 (0.215)	0.012 (0.043)
Age	-0.008 (0.005)	-0.002 $(0.001)^{*}$
Household size	0.039 $(0.012)^{***}$	0.008 $(0.002)^{***}$
Off-farm	-0.176 (0.137)	-0.036 (0.028)
Education	-0.051 (0.134)	-0.011 (0.028)
Area owned	0.001 (0.012)	0.000 (0.003)
Implements index	-0.046 (0.079)	-0.010 (0.017)
Distance to road	-0.009 (0.007)	-0.002 (0.001)
Distance to market	-0.007 (0.006)	-0.002 (0.001)
Extension	1.901 $(1.018)^{*}$	0.586 $(0.329)^{*}$
Credit	0.852 $(0.493)^{*}$	0.257 (0.186)
Casamance AEZ	-0.283 (0.205)	-0.064 (0.050)
Delta AEZ	1.034 (0.720)	0.312 (0.266)
Extension residuals	-0.478 (0.562)	
Log Likelihood	-264.889	
Num. obs.	835	

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

4.2 Production Frontiers Estimates

The conventional and sample selection frontiers models estimates are respectively presented in tables 4 and 5 for the original unmatched data, and in tables 6 and 7 for the matched data. From the estimation of the stochastic frontier models with the pooled data, the likelihood ratio (LR) tests indicate the rejection of the null hypothesis of homogeneous technology between cooperatives members and non-members for both the unmatched data ($\chi^2(23) = 45.553$, $p < 0.01$) and for the matched data ($\chi^2(23) = 39.394$, $p < 0.05$) justifying the identification strategy of two separate production frontiers for cooperatives members and non-members. Furthermore, in the pooled estimation with both unmatched and matched data, the positive and significant effect of cooperative membership dummy on the frontier estimates suggests that agricultural cooperative membership enhance significantly the rice production. Abdul-Rahaman and Abdulai (2018) and Ma *et al.* (2018b) observed similar results respectively in Ghana and China. These results can be explained by the fact that cooperatives members, in general, have better access to farm inputs and technologies through their social networks, and therefore increase their productions.

Table 4: Conventional Estimates of Translog Production Frontier: Unmatched sample

	Pooled	Members	Non-Members	Metafrontier
Intercept	5.388 (0.676)***	3.731 (3.093)	5.242 (0.727)***	5.163 (0.223)***
Land	0.045 (0.208)	-0.591 (1.024)	0.136 (0.221)	0.057 (0.069)
Seeds	0.081 (0.214)	0.873 (0.749)	-0.023 (0.239)	0.149 (0.07)**
Fertilizers	0.08 (0.188)	0.065 (0.898)	0.227 (0.206)	0.074 (0.061)
Labor	0.114 (0.116)	0.504 (0.337)	0.02 (0.134)	0.128 (0.038)***
Land^2	-0.21 (0.042)***	-0.286 (0.288)	-0.212 (0.043)***	-0.199 (0.014)***
Seeds^2	0.062 (0.053)	0.14 (0.184)	0.04 (0.057)	0.047 (0.017)***
Fertilizers^2	0.15 (0.041)***	0.107 (0.166)	0.109 (0.051)**	0.152 (0.013)***
Labor^2	0.036 (0.019)*	0.171 (0.063)***	0.014 (0.021)	0.032 (0.006)***
Land×Seeds	0.087 (0.048)*	0.043 (0.164)	0.105 (0.051)**	0.077 (0.016)***
Land×Fertilizers	-0.004 (0.021)	0.041 (0.068)	-0.057 (0.027)**	-0.015 (0.007)**
Land×Labor	0.015 (0.022)	0.164 (0.126)	-0.01 (0.024)	0.018 (0.007)**
Seeds×Fertilizers	-0.023 (0.014)	-0.014 (0.047)	-0.015 (0.018)	-0.021 (0.005)***
Seeds×Labor	-0.022 (0.025)	-0.243 (0.107)**	0.016 (0.027)	-0.023 (0.008)***
Fertilizers×Labor	-0.045 (0.01)***	-0.051 (0.024)**	-0.053 (0.012)***	-0.04 (0.003)***
No Fertilizers	0.379 (0.395)	-0.153 (2.286)	0.592 (0.416)	0.466 (0.129)***
Certified Seeds	0.024 (0.089)	0.164 (0.202)	-0.106 (0.1)	0.105 (0.03)***
Cooperative	0.27 (0.091)***			
Rainfall 2016	-0.001 (0.000)***	-0.001 (0.000)***	0.000 (0.000)	-0.001 (0.000)***
Clay (%)	0.041 (0.009)***	0.032 (0.024)	0.038 (0.01)***	0.044 (0.003)***
Silt (%)	-0.026 (0.01)**	-0.025 (0.026)	-0.028 (0.011)**	-0.026 (0.003)***
Intercept				0.242 (0.037)***
Casamance AEZ				-0.11 (0.033)***
Delta AEZ				-0.273 (0.263)
Grains Bird				-0.239 (0.044)***
Drought				-0.098 (0.042)**
Early Rain Stop				0.019 (0.023)
σ_u	0.871 (0.081)***	1.141 (0.139)***	0.628 (0.15)***	0.002 (0.000)***
σ_v	0.646 (0.037)***	0.491 (0.083)***	0.707 (0.05)***	0.264 (0.007)1
$\rho(w, v)$				
Log likelihood	-1026.735	-186.883	-817.075	-73.356
Num. obs.	835	153	682	835

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

Table 5: Conventional Estimates of Translog Production Frontier: Matched sample

	Pooled	Members	Non-Members	Metafrontier
Intercept	5.266 (0.696)***	3.533 (3.532)	5.242 (0.727)***	5.123 (0.193)***
Land	0.037 (0.211)	-0.401 (1.309)	0.136 (0.221)	0.058 (0.062)
Seeds	0.128 (0.22)	0.493 (0.882)	-0.023 (0.239)	0.165 (0.065)**
Fertilizers	0.081 (0.193)	0.013 (1.035)	0.227 (0.206)	0.067 (0.058)
Labor	0.096 (0.12)	0.356 (0.406)	0.02 (0.134)	0.111 (0.036)***
Land^2	-0.214 (0.042)***	-0.323 (0.386)	-0.212 (0.043)***	-0.204 (0.012)***
Seeds^2	0.044 (0.054)	0.288 (0.221)	0.04 (0.057)	0.039 (0.016)**
Fertilizers^2	0.157 (0.042)***	0.169 (0.193)	0.109 (0.051)**	0.162 (0.013)***
Labor^2	0.035 (0.02)*	0.201 (0.07)***	0.014 (0.021)	0.031 (0.006)***
Land×Seeds	0.099 (0.049)**	0.014 (0.215)	0.105 (0.051)**	0.087 (0.014)***
Land×Fertilizers	-0.013 (0.022)	0.01 (0.083)	-0.057 (0.027)**	-0.02 (0.007)***
Land×Labor	0.01 (0.023)	0.125 (0.145)	-0.01 (0.024)	0.014 (0.007)**
Seeds×Fertilizers	-0.031 (0.016)**	-0.053 (0.059)	-0.015 (0.018)	-0.028 (0.004)***
Seeds×Labor	-0.018 (0.025)	-0.245 (0.123)**	0.016 (0.027)	-0.021 (0.007)***
Fertilizers×Labor	-0.043 (0.01)***	-0.029 (0.027)	-0.053 (0.012)***	-0.04 (0.003)***
No Fertilizers	0.375 (0.399)	0.178 (2.626)	0.592 (0.416)	0.428 (0.12)***
Certified Seeds	0.005 (0.093)	0.233 (0.26)	-0.106 (0.1)	0.071 (0.028)**
Cooperative	0.255 (0.096)***			
Rainfall 2016	-0.001 (0)***	-0.001 (0)**	0 (0)	-0.001 (0)***
Clay (%)	0.042 (0.009)***	0.055 (0.028)*	0.038 (0.01)***	0.044 (0.002)***
Silt (%)	-0.027 (0.011)***	-0.041 (0.031)	-0.028 (0.011)**	-0.029 (0.003)***
Intercept				0.175 (0.017)***
Casamance AEZ				-0.06 (0.017)***
Delta AEZ				-0.821 (0.053)***
Grains Bird				-0.343 (0.012)***
Drought				-0.081 (0.002)***
Early Rain Stop				0.009 (0.006)
σ_u	0.834 (0.09)***	1.088 (0.169)***	0.628 (0.15)***	0.000 (0.000)***
σ_v	0.662 (0.04)***	0.553 (0.093)***	0.707 (0.05)***	0.248 (0.006)1
$\rho(w, v)$				
Log likelihood	-967.529	-130.757	-817.075	-18.874
Num. obs.	787	105	682	787

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

Table 6: Sample Selection Estimates of the Translog Production Frontier: Unmatched sample

	Members	Non-Members	Metafrontier
Intercept	3.633(5.867)	5.247(0.936)***	4.974 (0.374)***
Land	-0.936(1.284)	0.13(0.265)	0.008 (0.076)
Seeds	0.996(1.13)	-0.006(0.266)	0.221 (0.017)***
Fertilizers	0.08(1.63)	0.242(0.281)	0.121 (0.054)**
Labor	0.504(0.597)	0.036(0.172)	0.155 (0.036)***
Land^2	-0.37(0.401)	-0.213(0.056)***	-0.21 (0.018)***
Seeds^2	0.138(0.265)	0.039(0.059)	0.04 (0.02)**
Fertilizers^2	0.125(0.307)	0.11(0.064)*	0.148 (0.023)***
Labor^2	0.178(0.102)*	0.011(0.023)	0.033 (0.005)***
Land×Seeds	0.084(0.228)	0.106(0.057)*	0.083 (0.019)***
Land×Fertilizers	0.052(0.089)	-0.044(0.032)	-0.007 (0.008)
Land×Labor	0.188(0.169)	-0.009(0.031)	0.022 (0.01)**
Seeds×Fertilizers	-0.034(0.059)	-0.02(0.017)	-0.026 (0.004)***
Seeds×Labor	-0.25(0.185)	0.014(0.032)	-0.033 (0.007)***
Fertilizers×Labor	-0.056(0.047)	-0.055(0.015)***	-0.039 (0.004)***
No Fertilizers	-0.266(4.124)	0.549(0.671)	0.526 (0.071)***
Certified Seeds	0.166(0.299)	-0.141(0.109)	0.128 (0.037)***
Cooperative			
Rainfall 2016	-0.001(0.001)	0(0)	-0.001 (0)***
Clay (%)	0.033(0.032)	0.036(0.011)***	0.044 (0.004)***
Silt (%)	-0.026(0.035)	-0.03(0.013)**	-0.029 (0.005)***
Intercept			0.273 (0.047)***
Casamance AEZ			-0.139 (0.046)***
Delta AEZ			-0.322 (0.058)***
Grains Bird			-0.244 (0.166)
Drought			-0.114 (0.051)**
Early Rain Stop			0.03 (0.061)
σ_u	1.188(0.155)***	0.73(0.125)***	0.001 (0.000)***
σ_v	0.544(0.139)***	0.694(0.043)***	0.359 (0.004)1
$\rho(w, v)$	-0.475(0.46)	0.502(0.249)**	
Log likelihood			-313.359
Num. obs.	153	682	835

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

Table 7: Sample Selection Estimates of the Translog Production Frontier: Matched sample

	Members	Non-Members	Metafrontier
Intercept	4.722(7.355)	5.236(0.935)***	5.318 (0.389)***
Land	-0.807(1.83)	0.13(0.265)	0.036 (0.117)
Seeds	0.683(1.312)	-0.011(0.267)	0.179 (0.122)
Fertilizers	-0.157(1.99)	0.24(0.28)	0.081 (0.106)
Labor	0.311(0.795)	0.037(0.171)	0.131 (0.066)**
Land^2	-0.454(0.53)	-0.213(0.056)***	-0.21 (0.023)***
Seeds^2	0.268(0.344)	0.04(0.06)	0.041 (0.029)
Fertilizers^2	0.22(0.357)	0.11(0.064)*	0.169 (0.023)***
Labor^2	0.203(0.125)	0.011(0.023)	0.025 (0.011)**
Land×Seeds	0.072(0.32)	0.106(0.057)*	0.083 (0.027)***
Land×Fertilizers	0.038(0.105)	-0.047(0.032)	-0.019 (0.012)
Land×Labor	0.135(0.221)	-0.009(0.031)	0.018 (0.013)
Seeds×Fertilizers	-0.08(0.095)	-0.019(0.017)	-0.026 (0.009)***
Seeds×Labor	-0.242(0.195)	0.014(0.032)	-0.024 (0.014)*
Fertilizers×Labor	-0.04(0.063)	-0.054(0.015)***	-0.041 (0.006)***
No Fertilizers	-0.699(4.941)	0.562(0.667)	0.504 (0.223)**
Certified Seeds	0.24(0.523)	-0.132(0.108)	0.118 (0.051)**
Cooperative			
Rainfall 2016	0(0.001)	0(0)	0 (0)***
Clay (%)	0.047(0.04)	0.036(0.011)***	0.039 (0.005)***
Silt (%)	-0.04(0.047)	-0.029(0.013)**	-0.037 (0.006)***
Intercept			0.354 (0.062)***
Casamance AEZ			-0.054 (0.054)
Delta AEZ			-0.618 (0.102)***
Grains Bird			-0.239 (0.028)***
Drought			-0.181 (0.055)***
Early Rain Stop			0.053 (0.041)
σ_u	1.067(0.282)***	0.721(0.13)***	0.000 (0.000)***
σ_v	0.763(0.245)***	0.696(0.044)***	0.451 (0.012)1
$\rho(w, v)$	-0.768(0.235)***	0.475(0.299)	
Log likelihood			-489.258
Num. obs.	105	682	787

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

For all four production frontiers models, the inefficiency dispersion parameters σ_u are significant, suggesting that most of the farmers are producing below the production frontier. In addition, the terms σ_u in all models are much larger for the members of the cooperative than non-members, suggesting that the members of the cooperative are more affected by inefficiency than non-members. Results from the sample selection production frontiers models show that the estimated sample selectivity term ρ for members is negative and relatively high (in absolute terms) with both the unmatched and matched data, and statistically significant in the matched data estimation. This would suggest that unobserved factors that affect the participation in cooperatives are correlated with the idiosyncratic error term of the stochastic frontier model. For non-members, the estimated ρ is positive both matched and unmatched data, and only statistically significant in the case of the unmatched data, indicating the presence of selectivity bias from unobserved factors. These results support the use of the sample selectivity framework (Greene, 2010).

4.3 Predicted Frontiers

Table 8 presents the means of the predicted frontiers for all four models and the differences between the predicted frontiers of cooperatives members and those of non-members. The results of this table reveal that members of cooperatives have higher production frontiers than non-members and the differences are statistically significant. From estimates with the matched data, being a member increases the production of rice by around 17% in the conventional estimates of the stochastic production frontier model and when selectivity bias is taken into account, the increase reaches 27%. These figures confirm the previous results that cooperative membership increases rice production. These results corroborate those observed by Abdul-Rahaman and Abdulai (2018) in the rice sector in Ghana, where the participation in farmers group significantly enhances rice farming yield.

Table 8: Predicted frontier

SF Models	Pooled	Members	Non-Members	Difference
Unmatched				
Conventional	6.942(1.082)	7.957(1.185)	6.569(0.971)	1.388***
Sample Selection	6.875(1.176)	8.211(1.097)	6.575(0.967)	1.637***
Matched				
Conventional	6.829(1.035)	7.661(1.263)	6.569(0.971)	1.092***
Sample Selection	6.819(1.167)	8.407(1.104)	6.575(0.969)	1.832***

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

4.4 Technical Efficiency Score and Meta-Technology Ratios

Tables 9, 10 and 11 present the means of technical efficiency scores (TE) , the meta-technology ratios (MTR), and the meta-frontier technical efficiency derived from the estimated different production frontiers (respectively pooled, groups and meta frontier models). While figures 2 and 3 show respectively their distributions. Considering the pooled data estimates with the unmatched, in average cooperatives members and non-members have similar mean score of respectively 56.36% (SD=15.22%) [8] and 56.40% (SD=13.75%), proved by the non statistically t test difference ($t = -0.030, df = 211.91, p = 0.9757$). The non statistical difference is also observed for the pooled matched data ($t = -0.254, df = 128.79, p - value = 0.800$).

When considering that members and non-members are operating with different technologies, in all separate models, the mean TE estimates for non-members, which varies from 57.6% to 64.6% are significantly higher than that of members (46.3% to 51.0%), even if the difference slightly reduces when we controlled for selection bias.

[8] SD is the Standard deviation

These results suggest that after controlling for biases arising from both observable and unobserved differences between cooperatives members and non-members in the production frontiers, non-members are performing better within their own frontier than members. Therefore, one can conclude that considering the group-specific frontiers, membership in a cooperative has a strong negative causal effect on technical efficiency. These results contradict mainly those results recently obtained by Abdul-Rahaman and Abdulai (2018) and Ma *et al.* (2018b), who stopped their analysis at this stage of our methodological framework and found that members in cooperatives are more technically efficient in their own frontiers than non-members. As stated previously, comparing farmers' technical efficiencies from their own benchmark could bias the results. Technical efficiency estimates of cooperatives members and non-members are measured against different production frontiers.

Table 9: Levels of Technical efficiency (TE)

SF Models	Pooled	Members	Non-Members	Difference
Unmatched				
Conventional	0.564(0.14)	0.499(0.186)	0.646(0.096)	-0.147***
Sample Selection	0.555(0.141)	0.463(0.182)	0.576(0.121)	-0.113***
Matched				
Conventional	0.575(0.134)	0.51(0.172)	0.646(0.096)	-0.136***
Sample Selection	0.566(0.132)	0.482(0.169)	0.579(0.12)	-0.097***

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

The results from the meta-frontier estimates show that the meta-technology ratios of members in all four models (ranging from 84.2% to 94.3%) are significantly higher than those of non-members (ranging from 77.2% to 90.8%), suggesting that cooperatives members operate more closer to the meta-frontier than non-members. Therefore, one can conclude that membership in a cooperative affects strongly and positively the output of rice farming, confirming some of the previous results.

Table 10: Levels of Meta-technology Ratios (MTR)

SF Models	Pooled	Members	Non-Members	Difference
Unmatched				
Conventional	0.895(0.066)	0.943(0.076)	0.884(0.059)	0.058***
Sample Selection	0.889(0.072)	0.937(0.082)	0.878(0.064)	0.060***
Matched				
Conventional	0.908(0.05)	0.941(0.061)	0.903(0.047)	0.038***
Sample Selection	0.772(0.091)	0.842(0.118)	0.761(0.081)	0.081***

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

After combining the meta-technology ratios and the group technical efficiencies, the obtained mean of the meta-technology technical efficiencies estimates of the cooperatives' members varies between 41.0% (matched selectivity corrected) and 48.3% (matched conventional). These MTE estimates in all models for members are significantly lower than those of non-members. These results confirm some of the previous results and mainly suggest that after correcting for selectivity bias, belonging to a cooperative does not enhance farm efficiency.

Table 11: Levels of Metafrontier Technical efficiency (MTE)

SF Models	Pooled	Members	Non-Members	Difference
Unmatched				
Conventional	0.554(0.125)	0.473(0.185)	0.572(0.098)	-0.099***
Sample Selection	0.494(0.134)	0.436(0.18)	0.507(0.118)	-0.07***
Matched				
Conventional	0.57(0.114)	0.483(0.172)	0.584(0.096)	-0.101***
Sample Selection	0.438(0.119)	0.41(0.164)	0.442(0.109)	-0.031*

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

5 Conclusion

Farmers in developing countries are characterized by remarkably low levels of productivity and efficiency, mainly due to the lack of access to inputs and improved technologies. Therefore, cooperatives can constitute the vehicle for access to farm inputs and therefore enhance farm productivity. However, despite the growing literature on the importance of cooperative in developing countries, very few studies have investigated the impact that cooperatives can have on farmers' technical efficiency. This paper aimed to fill the gap by evaluating the quantitative effects of cooperative membership on farmers' technical efficiency in Senegal, where the access to modern technologies and productivity and efficiency in the rice sector are crucial issues.

Applying a econometric framework that combines a propensity score matching (PSM) method with the selection corrected stochastic production frontier model and a meta-frontier approach, on a cross-sectional data of 835 individuals, we derived for two groups of farmers (cooperatives members and cooperatives non-members) their group-specific technical efficiency scores, the meta-technology ratios, and the meta-technology technical efficiency. The PSM method enables us to match cooperatives members with non-members, addressing the biases from observed variables. With the selectivity-corrected stochastic production frontier model, the biases arising from unobserved were controlled. The meta-frontier approach helps to compare the technical efficiency score of both groups.

Estimations results confirmed that selection bias was present, and the two groups are using two different technologies for rice production, therefore justifying the combined framework that we used. The analysis shows that cooperatives membership affect positively and significantly the production of rice in Senegal, confirming the importance of cooperatives in developing countries and their roles in enhancing farm productions. However, non-members are technically more efficient than non-members when each group operates in its own frontier, contradicting recent studies.

The rest of the analysis shows that members have higher meta-technology ratios, meaning that they are operating much closer to the meta-frontier than non-members. In addition, in regard to the meta-frontier, significant differences are observed between cooperatives members and non-members, again in favor of non-members.

These results involve some policy implications. Cooperatives are still good instrumental tools to enhance farm productions in developing countries, by easing farm inputs and modern technologies. However, not all farmers benefit from being members of cooperatives, showed by the group-specific inefficiency scores. Therefore, policy-makers could exploit the derived social networks from cooperative to enable farmers to have better access to technical knowledge in order to highly increase farm productivity and efficiency, not only for members but also for non-members through their "natural" social networks (family, religion, geographic, etc). Further researches, could also investigate the spillover effects of cooperatives membership on non-members productivity and efficiency.

References

Abate, G. T., Francesconi, G. N. and Getnet, K. (2014) Impact of agricultural cooperatives on smallholders' technical efficiency: empirical evidence from Ethiopia, *Annals of Public and Cooperative Economics*, **85**.

Abdul-Rahaman, A. and 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.

Abebaw, D. and Haile, M. G. (2013) The impact of cooperatives on agricultural technology adoption: Empirical evidence from Ethiopia, *Food Policy*, **38**.

Addai, K. N., Owusu, V. and Danso-Abbeam, G. (2014) Effects of farmer-based-organization on the technical efficiency of maize farmers across various agro-ecological zones of ghana, *Journal of Economics*, **2**, 141–161.

Ahmed, M. H. and Mesfin, H. M. (2017) The impact of agricultural cooperatives membership on the wellbeing of smallholder farmers: empirical evidence from eastern Ethiopia, *Agricultural and Food Economics*, **5**.

Aigner, D., Lovell, C. and Schmidt, P. (1977) Formulation and estimation of stochastic frontier production function models, *Journal of Econometrics*, **6**, 21 – 37.

Balasubramanian, V., Sie, M., Hijmans, R. and Otsuka, K. (2007) Increasing rice production in sub-saharan africa: Challenges and opportunities, in *Advances in Agronomy* (Ed.) D. L. Sparks, Academic Press, vol. 94 of *Advances in Agronomy*, pp. 55 – 133.

Barham, J. and Chitemi, C. (2009) Collective action initiatives to improve marketing performance: Lessons from farmer groups in Tanzania, *Food Policy*, **34**, 53 – 59, collective Action for Smallholder Market Access.

Battese, G. E. (1997) A note on the estimation of cobb-douglas production functions when some explanatory variables have zero values, *Journal of Agricultural Economics*, **48**, 250–252.

Bernard, T. and Spielman, D. J. (2009) Reaching the rural poor through rural producer organizations? a study of agricultural marketing cooperatives in Ethiopia, *Food Policy*, **34**, 60 – 69.

Bernard, T., Taffesse, A. S. and Gabre-Madhin, E. (2008) Impact of cooperatives on smallholders' commercialization behavior: evidence from Ethiopia, *Agricultural Economics*, **39**, 147–161.

Bravo-Ureta, B. E., Greene, W. and Solís, D. (2012) Technical efficiency analysis correcting for biases from observed and unobserved variables: an application to a natural resource management project, *Empirical Economics*, **43**, 55–72.

Caliendo, M. and Kopeinig, S. (2008) Some practical guidance for the implementation of propensity score matching, *Journal of Economic Survey*, **22**, 31.

Chagwiza, C., Muradian, R. and Ruben, R. (2016) Cooperative membership and dairy performance among smallholders in Ethiopia, *Food Policy*, **59**, 165–173.

de Mey, Y., Demont, M. and Diagne, M. (2012) Estimating bird damage to rice in africa: Evidence from the Senegal River Valley, *Journal of Agricultural Economics*, **63**, 175–200.

Diagne, M., Demont, M., Seck, P. A. and Diaw, A. (2013) Self-sufficiency policy and irrigated rice productivity in the Senegal River Valley, *Food Security*, **5**, 55–68.

FAO (2019) Faostat.

Fischer, E. and Qaim, M. (2012a) Gender, agricultural commercialization, and collective action in Kenya, *Food Security*, **4**, 441–453.

Fischer, E. and Qaim, M. (2012b) Linking smallholders to markets: Determinants and impacts of farmer collective action in Kenya, *World Development*, **40**, 1255–1268.

Francesconi, G. N. and Heerink, N. (2010) Ethiopian agricultural cooperatives in an era of global commodity exchange: Does organisational form matter?, *Journal of African Economies*, **20**, 153–177.

Francesconi, G. N. and Ruben, R. (2012) The Hidden Impact of Cooperative Membership on Quality Management: A Case Study from the Dairy Belt of Addis Ababa, *Journal of Entrepreneurial and Organizational Diversity*, **1**.

González-Flores, M., Bravo-Ureta, B. E., Solís, D. and Winters, P. (2014) The impact of high value markets on smallholder productivity in the ecuadorean sierra: A stochastic production frontier approach correcting for selectivity bias, *Food Policy*, **44**, 237 – 247.

Greene, W. (2010) A stochastic frontier model with correction for sample selection, *Journal of Productivity Analysis*, **34**, 15–24.

Henningsen, A., Mpeta, D. F., Adem, A. S., Kuzilwa, J. A. and Czekaj, T. G. (2015) A meta-frontier approach for causal inference in productivity analysis: The effect of contract farming on sunflower productivity in tanzania, 2015 AAEA & WAEA Joint Annual Meeting, July 26-28, San Francisco, California 206200, Agricultural and Applied Economics Association.

Huang, C. J., Huang, T.-H. and Liu, N.-H. (2014) A new approach to estimating the metafrontier production function based on a stochastic frontier framework, *Journal of Productivity Analysis*, **42**, 241–254.

Ito, J., Bao, Z. and Su, Q. (2012) Distributional effects of agricultural cooperatives in China: Exclusion of smallholders and potential gains on participation, *Food Policy*, **37**, 700–709.

Jelliffe, J. L., Bravo-Ureta, B. E., Deom, C. M. and Okello, D. K. (2018) Adoption of High-Yielding Groundnut Varieties: The Sustainability of a Farmer-Led Multiplication-Dissemination Program in Eastern Uganda, *Sustainability*, **10**.

Jondrow, J., Lovell, C. K., Materov, I. S. and Schmidt, P. (1982) On the estimation of technical inefficiency in the stochastic frontier production function model, *Journal of Econometrics*, **19**, 233 – 238.

Kumbhakar, S. C., Tsionas, E. G. and Sipiläinen, T. (2009) Joint estimation of technology choice and technical efficiency: an application to organic and conventional dairy farming, *Journal of Productivity Analysis*, **31**, 151–161.

Ma, W. and Abdulai, A. (2016) Does cooperativemembership improve household welfare? Evidence from apple farmers in China, *Food Policy*, **58**, 94–102.

Ma, W., Abdulai, A. and Goetz, R. (2018a) Agricultural Cooperatives and Investment in Organic Soil Amendments and Chemical Fertilizer in China, *American Journal of Agricultural Economics*, **100**, 502–520.

Ma, W., Renwick, A., Yuan, P. and Ratna, N. (2018b) Agricultural cooperative membership and technical efficiency of apple farmers in China: An analysis accounting for selectivity bias, *Food Policy*, **81**, 122 – 132.

Mayen, C. D., Balagtas, J. V. and Alexander, C. E. (2010) Technology adoption and technical efficiency: Organic and conventional dairy farms in the united states, *American Journal of Agricultural Economics*, **92**, 181–195.

Mishra, A. K., Kumar, A., Joshi, P. K. and D'Souza, A. (2018) Cooperatives, contract farming, and farm size: The case of tomato producers in Nepal, *Agribusiness*, **34**, 865–886.

Mojo, D., Fischer, C. and Degefa, T. (2017) The determinants and economic impacts of coffee farmer cooperatives: Recent evidence from rural Ethiopia, *Journal of Rural Studies*, **50**, 84–94.

Rosenbaum, P. R. and Rubin, D. B. (1983) The central role of the propensity score in observational studies for causal effects, *Biometrika*, **70**, 41.

République du Sénégal (2009) Programme National d'Autosuffisance en Riz, Tech. rep., Ministère de l'Agriculture.

Salifu, A., Francesconi, G. N. and Kolavalli, S. (2010) A review of collective action in rural Ghana, Tech. Rep. 998, International Food Policy Research Institute (IFPRI).

Seck, P. A., Tollens, E., Wopereis, M. C., Diagne, A. and Bamba, I. (2010) Rising trends and variability of rice prices: Threats and opportunities for sub-Saharan Africa, *Food Policy*, **35**, 403 – 411.

Tolno, E., Kobayashi, H., Ichizen, M., Esham, M. and Balde, B. S. (2015) Economic analysis of the role of farmer organizations in enhancing smallholder potato farmers' income in middle guinea, *Journal of Agricultural Science*, **7**.

Verhofstadt, E. and Maertens, M. (2015) Can Agricultural Cooperatives Reduce Poverty? Heterogeneous Impact of Cooperative Membership on Farmers' Welfare in Rwanda, *Applied Economic Perspectives and Policy*, **37**, 86–106.

Villano, R., Bravo-Ureta, B., Solís, D. and Fleming, E. (2015) Modern rice technologies and productivity in the philippines: Disentangling technology from managerial gaps, *Journal of Agricultural Economics*, **66**, 129–154.

Wollni, M. and Zeller, M. (2007) Do farmers benefit from participating in specialty markets and cooperatives? the case of coffee marketing in Costa Rica, *Agricultural Economics*, **37**, 243–248.

Wooldridge, J. (2015) Control function methods in applied econometrics, *Journal of Human Resources*, **50**, 420–445.

World Bank (2007) *World Development Report 2008 : Agriculture for Development*, World Bank Washington, DC.

Appendix

Table A1: Propensity score of cooperative membership

	Unmatched Sample	Matched Sample
Intercept	$-1.134\ (0.471)^{**}$	$-0.990\ (0.494)^{**}$
Sex	$0.057\ (0.215)$	$0.018\ (0.217)$
Age	$-0.008\ (0.005)$	$-0.009\ (0.005)^{*}$
Household size	$0.039\ (0.012)^{***}$	$0.039\ (0.012)^{***}$
Off-farm	$-0.176\ (0.137)$	$-0.138\ (0.140)$
Education	$-0.051\ (0.134)$	$-0.060\ (0.135)$
Area owned	$0.001\ (0.012)$	$-0.003\ (0.014)$
Implements index	$-0.046\ (0.079)$	$-0.014\ (0.083)$
Distance to road	$-0.009\ (0.007)$	$-0.009\ (0.007)$
Distance to market	$-0.007\ (0.006)$	$-0.007\ (0.006)$
Extension	$1.901\ (1.018)^{*}$	$1.402\ (1.155)$
Credit	$0.852\ (0.493)^{*}$	$0.684\ (0.576)$
Casamance AEZ	$-0.283\ (0.205)$	$-0.249\ (0.220)$
Delta AEZ	$1.034\ (0.720)$	$0.961\ (0.805)$
Extension residuals	$-0.478\ (0.562)$	$-0.298\ (0.637)$
Log Likelihood	-264.889	-252.521
Deviance	529.779	505.042
Num. obs.	835	787

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

Table A2: Balancing test results of PSM.

	Members	Non-Members	P-values	Members	Non-Members	P-values	% Red Bias
Sex	0.93	0.89	0.16	0.92	0.88	0.26	-10.10
Age	52.58	53.81	0.28	52.50	51.30	0.44	3.20
Household size	10.33	94.93	0.07	10.37	10.04	0.62	60.80
Off-farm	0.28	0.44	0.00	0.29	0.28	0.93	97.00
Education	0.58	0.52	0.19	0.56	0.66	0.11	-63.80
Area owned	29.96	36.78	0.18	29.22	27.12	0.66	69.20
Implements index	-1.16	-0.97	0.01	-1.12	-11.96	0.55	62.90
Distance to road	17.16	97.91	0.00	18.07	18.45	0.87	94.90
Distance to market	17.09	15.71	0.23	17.09	19.50	0.22	-74.90
Extension	0.61	0.10	0.00	0.56	0.55	0.82	97.30
Credit	0.06	0.01	0.00	0.04	0.05	0.67	78.40
Casamance AEZ	0.40	0.84	0.00	0.46	0.50	0.55	91.60
Delta AEZ	0.40	0.03	0.00	0.35	0.36	0.87	97.40

Table A3: Addressing potential endogeneity in extension variable

	Cooperative	Extension
Intercept	−0.634 (0.365)*	−0.828 (0.353)**
Sex	−0.024 (0.207)	−0.121 (0.191)
Age	−0.009 (0.005)*	−0.001 (0.005)
Household size	0.043 (0.011)***	0.016 (0.011)
Off-farm	−0.100 (0.126)	0.139 (0.120)
Education	−0.091 (0.127)	−0.082 (0.123)
Area owned	−0.009 (0.014)	−0.032 (0.018)*
Implements index	−0.050 (0.075)	−0.040 (0.074)
Distance to road	−0.012 (0.006)**	−0.012 (0.006)**
Distance to market	−0.010 (0.005)*	−0.009 (0.005)*
Credit	1.352 (0.340)***	1.090 (0.341)***
Number of plots	0.056 (0.040)	0.129 (0.041)***
Casamance AEZ	−0.531 (0.151)***	−0.530 (0.148)***
Delta AEZ	2.092 (0.289)***	2.077 (0.285)***
Log Likelihood	-291.481	-318.322
Num. obs.	835	835

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

Figure 1: Kernel density of propensity scores

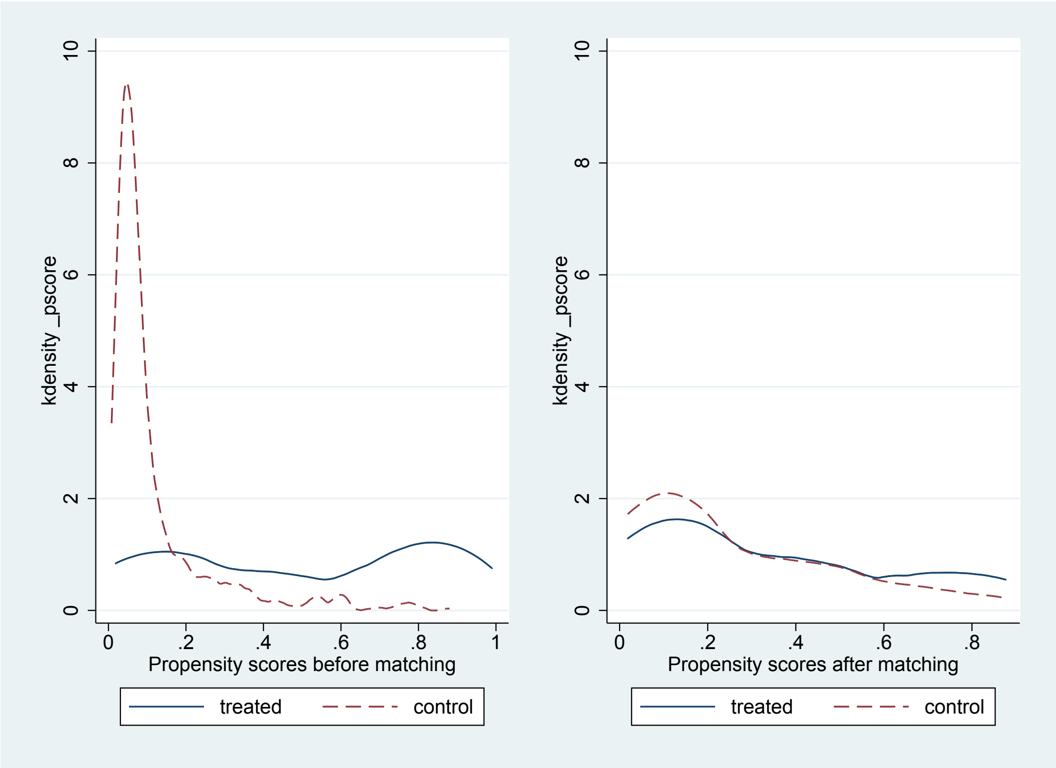

Table A4: Estimates of the Translog and Cobb-Douglas frontiers

	Translog	Cobb-Douglas
Intercept	5.388 (0.676)***	5.206 (0.398)***
Land	0.045 (0.208)	0.68 (0.041)***
Seeds	0.081 (0.214)	0.026 (0.038)
Fertilizers	0.08 (0.188)	0.377 (0.052)***
Labor	0.114 (0.116)	0.081 (0.024)***
Land^2	-0.21 (0.042)***	
Seeds^2	0.062 (0.053)	
Fertilizers^2	0.15 (0.041)***	
Labor^2	0.036 (0.019)*	
Land×Seeds	0.087 (0.048)*	
Land×Fertilizers	-0.004 (0.021)	
Land×Labor	0.015 (0.022)	
Seeds×Fertilizers	-0.023 (0.014)	
Seeds×Labor	-0.022 (0.025)	
Fertilizers×Labor	-0.045 (0.01)***	
No Fertilizers	0.379 (0.395)	1.529 (0.232)***
Certified Seeds	0.024 (0.089)	-0.055 (0.091)
Cooperative	0.27 (0.091)***	0.23 (0.093)**
Rainfall 2017	-0.001 (0)***	-0.001 (0)***
Clay (%)	0.041 (0.009)***	0.049 (0.009)***
Silt (%)	-0.026 (0.01)**	-0.026 (0.01)**
σ_u	0.871 (0.081)***	0.881 (0.094)***
σ_v	0.646 (0.037)***	0.691 (0.042)***
Log likelihood	-1026.735	-1066.375
Num. obs.	835	835

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

Figure 2: Distributions of estimated efficiency scores (TE)

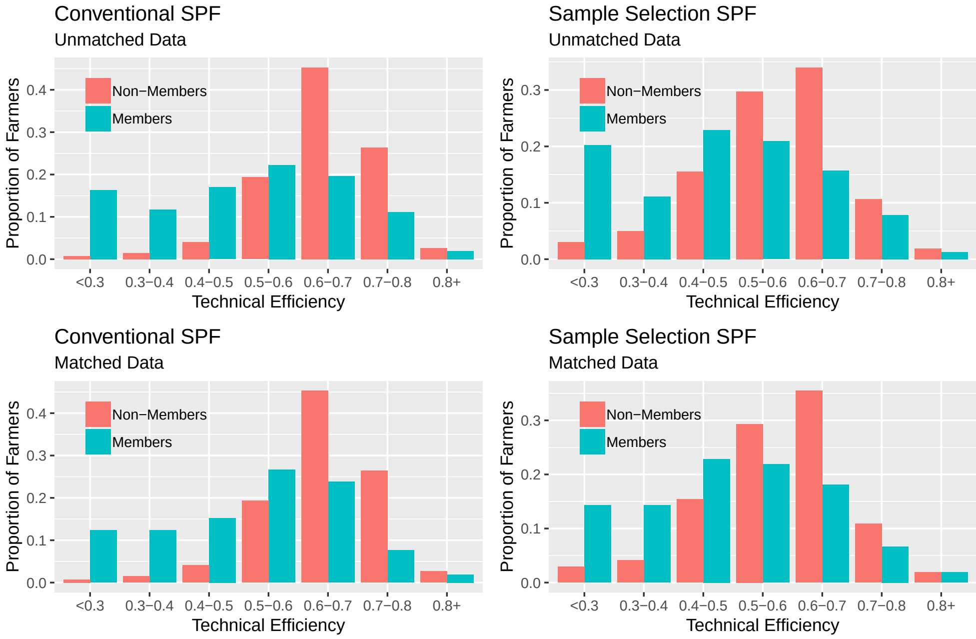

Figure 3: Distributions of estimated Meta Technology Efficiency scores (MTE)