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Abstract

This paper investigates the empirical causal relationship between farmers organizations membership and food availability in Senegal. Using a unique country scale farm-level data of cereals farming households, and applying various econometrics estimations techniques that control for selection biases and spatial heterogeneity, the study found positive and significant association between organizations membership and farmers levels of cereals production. Findings are consistent across estimations methods. Being a member of an farmer organization increases cereals production by 19%. These results suggest once again the importance of farmers organizations in the fight against rural food insecurity. In addition, other factors such as the access to extension services, fertilizer subsidies and the rainfall appear to be significantly determining households food production. Furthermore, results also reveal the relevance of spatiality in the analysis of agricultural sector in developing countries.

Keywords: farmers organizations, impact evaluation, spatial heterogeneity
JEL classification: Q130

1 Introduction

Food insecurity remains a serious concern in Sub-Saharan Africa (SSA). According to FAO *et al.* (2019), the hunger prevalence in that region in 2018 is estimated at 22.8% and about 240 million of people are concerned. Senegal is one this SSA countries with approximately 15 million people, which experienced significant and steady economic growth since 2014, with a average GDP growth of 6.64% from 2014 to 2018 (World Bank, 2019). However, according to the 2019 Human Development Index, the country ranked at 166 out of 189, indicating a low human development level in 2018. In addition, poverty rates are still high, 53.2 percent of the population are considered multidimensionally poor (UNDP, 2019). Moreover, during the period 2016-18, about 11.3 % (1.8 million of people) of the Senegalese population have suffered from hunger (FAO *et al.*, 2019), and figures from the 2013 census indicated that poverty is mostly prevalent in rural areas where the primary source of income and food is agriculture (Republique du Senegal, 2014).

Food security is commonly defined as the situation "when all people, at all times, have physical, social and economic access to sufficient, safe and nutritious food that meets their dietary needs and food preferences for an active and healthy life" (FAO *et al.*, 2019, p.186). This generally accepted definition implies four dimensions: food availability, economic and physical access to food, food utilization and stability over time. The first dimension involves primarily substantial food production at the domestic level. However, in the context of Senegal, food production which is regularly affected by climatic shocks remains at low levels.

According to McArthur and McCord (2017)'s works, agricultural productivity can play a strong role in driving structural change. Increasing farm productivity and agricultural production could therefore, constitute a primary way of ensuring and improving food security and living conditions in rural areas. However, due to inadequate access to improved technologies, Senegalese agriculture is still at the subsistence state. Figures show that in 2015, Senegal was far below the Sub-Saharan averages of cereals yields and agricultural value added per worker (Hathie *et al.*, 2017).

Accessing production inputs and technologies are general challenges for agricultural sectors in most developing countries (World Bank, 2007). Nevertheless, producers organizations could help alleviating such burdens, by playing their expected role, as mechanisms of reduction of transaction costs (Latynskiy and Berger, 2016). According to Bernard *et al.* (2015), in developing countries, these farmers-based organizations can provide smallholders with better access to production inputs. In addition, results from previous empirical studies show that, farmers collective action groups improve significantly commercialization rates (Barham and Chitemi, 2009; Chagwiza *et al.*, 2016), technologies adoption levels (Abebaw and Haile, 2013; Ma *et al.*, 2018), households welfare (Fischer and Qaim, 2012), and food security (Zeweld *et al.*, 2015). Nonetheless, studies of Bernard *et al.* (2008b), Francesconi and Heerink (2010), and Hoken and Su (2015) did not find any positive association between farmers organizations and commercialization rates or farms productions.

Furthermore, previous studies did not control for the potential biases stemming from the spatial features of the farmer's specific location. In general, the potential effect of proximity among farmers is usually ignored in impact studies. However the magnitude of these effects might be significant in farming settings in developing countries. To highlight the importance of spatiality, let consider the situation of extension services in most African contexts. With the aim of reaching most farmers, extension services usually target progressive farmers (Diagne, 2006), who are therefore better aware of new technologies and have a better access to them. Such strategy tends finally to favor some villages or communities than others. Therefore, in the same country, for a reason or another, some regions might be fully provided with active extension agents meanwhile some other would be barely covered. Such situation, which would reinforce the gap between regions' levels of technology adoption, would probably lead to significant differences in farmers productions.

The same argument holds as well for the difference in the other agricultural infrastructures or facilities among regions (road, markets, credits institutions, research institutes). Some communities might live closer to roads or markets that help them to have access to inputs and technologies with a certain ease. Meanwhile, other communities literally struggle to reach these purchasing points[1]. Moreover, agro-environmental features (e.g. temperature, rainfall, soil fertility) of the location of each farmer constitute structural conditions that might affect their decisions of technological choices and therefore their levels of productivity and food production. For instance, some Senegalese regions experience recurrent environmental shocks that constantly threaten or hamper agricultural production and therefore exacerbate household food security. According to Hathie *et al.* (2017), in Senegal, geography plays a important role in food security. Some regions in the country despite their natural endowments and economic potential are more prone to food insecurity, due to the lack and poor quality of transport infrastructure.

Such spatial heterogeneity that influences farmers yields in most cases are not observable to the analyst. As pointed out by LeSage and Pace (2009), amenities and characteristics of the location of a farmer usually constitute unobservable factors and might affect the performance of farmers, and it is difficult to find explanatory variables that capture easily and completely all types of these latent effects. Past studies on the impact of cooperatives membership assume independence between outcomes variables in neighboring farmers, without controlling for spatial heterogeneity. This approach presents some limitations that lead to biased results and inadequate policy recommendations that followed.

This paper applies a spatial econometric approach to determine the impact of farmers organizations membership on household food production in Senegal. The results contribute to an better understanding of the contribution of collective action groups and has several implications for policy recommendations that would take into account spatial heterogeneity in farming in Senegal. The remainder of this paper is organized as follows. The following two sections present briefly the context and background of the study, and a description of the empirical framework. The last

[1]See Wanmali and Islam (1997) and Jouanjean (2013) for better discussions on the impact of differential access to rural infrastructures on agriculture in developing countries.

sections present, discuss and summarize the estimations results.

2 Agriculture, food security and farmers organizations in Senegal

Agriculture is a key sector of the Senegalese economy. Although the country experienced a steady economic growth rate of 6.64% from 2014 to 2018, with a pic of 7.08% in 2017 (the highest since 1982) (World Bank, 2019), the economy remains largely dependent on the agricultural sector. In 2017, the sector occupies approximately 32% of the country's total employment, represents more than 16% of the national GDP (World Bank, 2019) and provides 21%[2] of the total country's exports (Republique du Senegal, 2018a). The contribution of the sector to GDP formation has gradually declined over the last forty years. However, since 2011, the trend has changed, from 12% in 2011 it reached 17% in 2018 (World Bank, 2019). Indeed, since 2012, the Senegalese agricultural policies and strategies (Programme d'Accélération de la Cadence de l'Agriculture Sénégalaise, PRACAS) put emphasis on a more competitive, diversified and sustainable agriculture (Republique du Senegal, 2018b).

Senegalese agriculture is mainly seasonal and rain-fed with nearly 9 out of 10 households practicing rain-fed cropping (Republique du Senegal, 2014). Main cultivated crops include cereals (rice, millet, maize and sorghum), groundnut, cotton and horticultural crops (Republique du Senegal, 2018b). The sector as noted by Fall (2016) faces several constraints, e.g. access to inputs, access to credit, lack of production and storage infrastructures. According to the general census of the population of 2013 (Republique du Senegal, 2014), the agricultural sector is principally driven by traditional small-scale farmers, which primarily (for nearly 74%) live in predominantly poor rural areas. These farmers are mainly organized into rural producers organizations which are mostly regarded, as a means to solve the problems of job security and social insurance (Fall, 2008).

The average poverty rate in rural areas is 57.3% against 46.7% for the whole country [3]. Results from the National Food Security Survey of 2016 (Enquete Nationale de Sécurite Alimentaire au Sénégal 2016 in french) (Republique du Senegal, 2016), show that about 12% of the population had limited and unsatisfactory food consumption, and about 5% have poor food consumption. In addition, the survey revealed that the prevalence of poor food consumption is four times higher in rural areas, compared to urban ones (7.9% versus 2.1%).

According to Bernard *et al.* (2015), 70% of rural households in Senegal are members of rural producer organizations, and these rural institutions have expanded rapidly during the last decades. In 2019, although it is difficult to have an accurate figure of the number of these farmers collective action groups, they have been

[2]Calculation is based on values of exportation figures in Republique du Senegal (2018a) and includes exports of fishes products, groundnut products, and cotton and cotton fabrics.

[3]Estimated by the Poverty Monitoring Survey in Senegal (ESPS-II) in 2013.

shaped through time resulting in various legal and institutional forms. As stated by Wanyama *et al.* (2009), the established cooperative model in Francophone area was the one that brought together people with common social and economic objectives.

The journey of the Senegalese cooperative movement started with the colonial ruler, where the 'societies indigenes de prévoyance' were introduced to increase cash crop production for export markets and to control economic activity in rural areas. From 1960, with the independence of the country, agricultural cooperatives were created and controlled by the government which mainly encouraged their development. These cooperatives served as the main vehicles and mechanisms (credit granting, inputs distribution, prices fixing) through which agricultural products are collected and purchased, putting therefore farmers under the dependence of the State (Gagné *et al.*, 2008). By the begin of 1980s, a sharp decline in the support offered by the State was observed, following the imposition of Structural Adjustment Policies by the World Bank. This situation resulted in a sort of inertia in the cooperative movement (Gagné *et al.*, 2008), and following the reform of the cooperative system in 1983 ("Nouvelle Politique Agricole"), non-governmental organizations other than cooperatives began to emerge especially the Economic Interest Groups (Groupement d'Interet Economiques, GIE)(Gaye, 1994). GIE were viewed as an alternative solution to failing cooperatives, emphasizing their economic aspects to the purely social considerations of cooperatives (Gaye, 1990). From the 1990s, Government disengagement contributes to a rapid development of cooperatives (Fall, 2008; Gagné *et al.*, 2008), which are seen as a means for vulnerable populations to solve their problems of job security and social insurance(Fall, 2008), and for governments and donors as a major channel to reach the rural poor (Bernard *et al.*, 2008a).

Since 2009, the cooperative movement is experiencing a revival, with the introduction of the Agro-Sylvo-Pastoral Law which provided both legal and financial support for agricultural cooperatives development (Reed and Hickey, 2016). This historical development led to various types of farmers organizations, which differ in their legal forms, their functions and the way they are organized.

3 Empirical Framework

We assume that there is an association between the farm household food availability and the membership in a rural producer organization or farmers organization (or farmers groups membership)[4]. We specified the following model of food availability as:

$$Y = f(C, E, X, W), \tag{1}$$

where Y represents the food availability of a household, and depends on producer organization membership (C), access to extension services E, other households characteristics X including environmental factors, and geographical proximity W. To estimate this model, we consider in our empirical strategy four specifications. In the first two, we assume that $W = 0$, therefore we applied an ordinary least squares

[4]We use the three expressions alternatively.

technique, and a two stage least squares instrumental variables method. For the last two specifications, we included in previous ones, spatial heterogeneity between observations via W.

3.1 Estimation Strategy

We first consider a linear regression model, specified as:

$$Y = \alpha + \gamma C + \theta E + \beta X + \epsilon, \tag{2}$$

where Y denotes a measure of the household food availability indicator; C is a binary variable for farmer organization membership; E is a binary variable for access to extension services; X is a k-dimensional vector of other explanatory variables; α, γ , θ, and β are the parameters to be determined and respectively associated with organization (or group) membership, extension and the control variables; and ϵ is the error term.

Assuming that $E[\epsilon|C, E, X] = 0$ (i.e. the errors are uncorrelated with any of the right hand side variables), we can apply the ordinary least squares technique (referred as OLS) to estimate all parameters mentioned above. Therefore, for any randomly selected household, the parameter of interest γ, would be interpreted as the average effect of farmer-based organizations membership on household food availability.

However, prior literature on farmers organizations and access to extension services have demonstrated the possible endogeneity of these two variables when estimating their effects on farms productions or incomes (Francesconi and Ruben, 2012; Wossen *et al.*, 2017; Ma and Abdulai, 2016). Therefore OLS technique will provide inconsistent estimates for these parameters and especially for the one of interest γ. Endogeneity of these variables is sourced in farmers self-selectivity in producer organizations or in accessing extension services. Farmers who are members of groups mostly self-select themselves to be members, rendering membership non-random. Farmers might be members of organizations or participate to extension services, due to some unobservables characteristics e.g. motivation; that are not controlled for in OLS regressions. Furthermore, membership in groups or the access to extension might be driven by farmers' level of food productivity. Farm households with low-average of food productivity would join organizations with the motivation to improve their level of food production, and farmers who have high-average food productions then join cooperatives because of their high level of food production. To control for biases that could stem from observable factors, we could include in the OLS specification as many as justifiable several exogenous control variables. However, for selection biases arising from unobservables, we could address it by the means of instrumental variable method.

The usual instrumental variables (IV) regression is a two stage estimation approach. However, empirically and similarly to Adams *et al.* (2009), the IV method adopted in this paper follows (Wooldridge, 2010, p: 937-942)'s three step approach of IV estimation with an endogenous dummy variable (referred as 2SLS-IV). In a first step, we estimate a probit model for each endogenous dummy variable (group membership and extension services) as functions of the respective instruments (solar grids and extension needs) and other control variables. In the second step, we regress each endogenous dummy variable (group membership and extension services) on the predicted probabilities from the fist step of the endogenous variables ($\hat{C}$ and $\hat{E}$), and X. In the third step, we regress Y on the predicted values of the second step and the covariates (X). In other words, after the first step, the fitted probabilities are used as instruments for the endogenous dummies in a usual two Stages Least Squares IV estimation of equation (2). This estimation procedure exploits better the binary nature of our endogenous variables and produces more precise estimates. In addition, the usual 2SLS standard errors and test statistics are asymptotically valid (Wooldridge, 2010).

The 2SLS-IV technique requires at least valid instruments at the first stage of estimation. A valid instrument (Z) have to fulfill two important conditions: (i) the relevance i.e. it has to be significantly correlated with the endogenous variable (group membership or extension services) and, (ii) the exclusion restriction i.e. this instrument has to affect the food availability of farmers only through the endogenous variable. To instrument farmers membership in producer organizations, the study uses household ownership of solar grids. Thus, from the question: "what do you use as fuel for lightning?", we created a dummy variable "solar grids" which takes the value 1, if the household uses solar grids as lightning fuel and the value 0, otherwise. The use of solar grids expresses the inner motivation of farmers towards new technologies, predisposition to learn, to invest in a innovation or to take risk. Farmers who use solar grids are expected to participate actively in farmers groups. However, using solar grids as lightening fuel is not supposed to affect directly the household food indicators, but only through groups membership. Access to extension services is instrumented by the self-expression of farmers for the need for support. Similarly to the first instrument, 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 that he needs extension first and he needs supports and the value 0, otherwise. Farmers who needs to be supported are expected to have access to extension services, or at least exploring ways to have access to it.

To check for the validity of these instruments, we run separately, probit models of the endogenous binary variables C and E on Z and X (previously described as the first stage), and OLS regressions of the outcome on group membership, extension services, covariates X, and the instruments, and we have checked the significance of the instruments coefficients. Here as argued by Adams *et al.* (2009), the IV approach does not require the probit specifications to be correct, its only requires the designed instrument to be correlated with the endogenous variable. Results of the probit estimations, in table 3, show that the suggested instruments are positively correlated respectively with group membership ($z = 2.848$, p-value < 0.01) and extension services ($z = 4.258$, p-value < 0.01). Therefore, we can conclude that our instruments are relevant. They affect the endogenous variables in the right and predicted direction, and they are strongly correlated to the endogenous variables. In addition, OLS regressions reveal that the instruments are not directly correlated with the outcome variable ($F = 0.623(2)$, p-value $= 0.536$, $F = 0.558(2)$, p-value $= 0.572$).

The implication of using the instrumental variables technique is that in this model, γ measures the local effect of group membership. This means that IV estimates of γ measures the impact of group membership for households that are affected in their choice to be members by the instrument (i.e. the use of solar grids).

As motivated previously, in the presence of spatial heterogeneity in cross-sectional data, non-spatial regression models violate the classical assumptions of the independence between observations. The error terms ϵ in equation 2 are no longer identically and independently distributed, therefore the obtained estimates are biased and inconsistent (Lesage, 2008). Once, the conventional assumption is relaxed, one have to find ways to model the structure of the dependence between observations. When unobserved and unobservable spatial features affect observations, the spatial heterogeneity of these features leads to spatially correlated errors. We assume therefore that $W \neq 0$, and estimate the spatial error model (referred as SEM). The SEM model accounts for spatial heterogeneity between farmers food availability outcome, it is specified as:

$$Y = \alpha + \gamma C + \theta E + \beta X + \epsilon \quad \text{with} \quad \epsilon = \lambda W \epsilon + \xi, \tag{3}$$

where Y, C, E, and X are defined as previously; α, γ, θ, β, and λ are parameters to be estimated respectively for group membership, extension services, the other control variables, and the spatial error lag; λ measures the spatial autocorrelation and is comprised between -1 and 1; ϵ and ξ are the error terms; and W is a prespecified $(N \times N)$ exogenous spatial weights matrix. Since ordinary least squares are assumed to produce non consistent estimates for spatial models (Lesage, 2008). The SEM model is estimated using the maximum likelihood estimation method (Ord, 1975; Anselin, 1988).

The spatial weight matrix W is a symmetric matrix, where its elements w_{ij} express closeness or proximity of a household i with a household j. In common practices, to enable an interpretation of model coefficients, W is row standardized so that the sum of the row elements equals one. In addition, the diagonal elements w_{ii} are set to zero, in order to prevent effect of the i household from directly predicting itself. Many specifications of weight matrices have been used in the literature, and specifying the weight matrix is arbitrary. However, the prior knowledge of the study population and economic theory can help to guide in the specification of these matrices. We consider in our study only one specification, the exact inverse distance matrix, which expresses the geographical proximity of farmers. Neighbors in this specification have different weights, and those with higher weights are closer in distance. In an inverse distance matrix W, elements w_{ij} are defined as $1/d_{ij}$, where d_{ij} is the euclidean distance between households i and j.

Finally, we also estimate the same SEM model (equation 3) by accounting this time for the endogeneity of group membership and access to extension services (referred as SEM-IV). As demonstrated by Betz *et al.* (2019), the widely used IV models generally ignore the spatial patterns of the outcome variables, leading in asymptotically biased estimates even when instruments are randomly assigned. Furthermore, if the instrument exhibits spatial patterns similar to that of the outcome (as in many popular instruments that are not randomly distributed across space), the bias in IV estimates increases, and sometimes, they are greater than that of ordinary least squares (Betz *et al.*, 2019). The Generalized spatial two-stage least squares method (GSTSLS) of (Kelejian and Prucha, 1998, 1999) was used to estimate the SEM-IV model. GSTSLS estimators are justified in our estimation strategy, due to the presence in our models, of two endogenous explanatory variables, group membership and access to extension, that need to be instrumented (Elhorst, 2010).

Before implementing the spatial error models, the spatial autocorrelation index Moran's I was employed to test whether there is a spatial correlation between farmers food availability outcome. Based on the spatial weights, Moran's I statistic is computed as:

$$I = (\sum_i \sum_j w_{ij}(Y_i - \bar{Y})(Y_j - \bar{Y}))/(\sum_i (Y_i - \bar{Y})^2), \tag{4}$$

where w_{ij} is a spatial weight between households i and j; Y_i represents the food availability outcome of household i; and $\bar{Y}$ is the mean of the food availability outcome. The range of Moran's I is $(-1, 1)$, with 1 indicating perfect spatial similarity (or positive spatial correlation), 0 indicating no spatial correlation, and -1 indicating perfect dispersion (or negative correlation). If we observe a significant spatial autocorrelation based on Moran's I statistic, spatial regressions models should be used to correct for the spatial autocorrelation errors. In addition, using residuals from the non-spatial OLS model, we also computed the standard Lagrange Multiplier (LM_{error}) test for spatial error correlation (Anselin *et al.*, 1996). The standard LM_{error} test is specified as:

$$LM_{error} = [e'We/(e'e/N)]^2/[tr(W^2 + W'W)] \tag{5}$$

where e denotes the estimated residual from the non-spatial model; N is the number of farmers; and W are defined as previously. The Maximum Likelihood method in the R package *spdep* (Bivand and Wong, 2018) was used to estimate the SEM model. Following Betz *et al.* (2019), the Generalized Spatial 2SLS built in the R package *sphet* Piras (2010) was used to estimate the SEM-IV.

3.2 Data Sources and Variables Description

The data used in this paper is primarily derived from a cross-sectional survey conducted in Senegal, which randomly sampled 4533 households that mainly produce rainfed or dry cereals (millet, sorghum, maize, fonio, rainfed rice). The data was collected in 2017 in the framework of the Agricultural Policy Support Project (Projet d'Appui aux Politiques Agricoles, PAPA in French) funded by USAID. The Senegalese National Agricultural Research Institute (ISRA) conducted the survey, with the support of the International Food Policy Research Institute (IFPRI). A multi-stage sampling procedure was applied for the selection of households. Data covers the main agricultural season of 2016-2017. A structured household questionnaire was used and the collected information includes crop productions, rural producer organizations membership, household assets, access to infrastructure, access to rural institutions, use of agricultural technologies, and household demographic and socioeconomic characteristics, inputs use information, markets prices of both inputs and outputs, and climatic shocks. Surveyed households are located in all six agro-ecological zones.

Although the survey was directed towards cereals farming, many of the surveyed households did not produce (or did not report) cereals harvests for the season, we therefore restrained our sample to households that produce the main five cereals including millet, maize, rainfed rice, sorghum and fonio. These crops are also the principal elements of rural households diet. The final sample comprises then 3939 farm households.

Table 2 presents the definition and summary statistics of the variables used in the analysis. The total production of cereals crops during the whole season (referred hereafter as cereals production), is used to proxy household food availability. This dependent variable, expressed in West African Franc (FCFA)[5] represents the gross value of all cereals productions valued at the market prices. The considered cereals are millet, maize, rice, sorghum and fonio. This approach is more suitable to compare farmers, since most cereals productions are not marketed by farmers, and their weights are not valued at the same market price. In addition, cereals grains represent a large proportion of the dietary energy supply especially in rural areas. Farmers in our sample produce in average 1315 kg of cereals (of which 622 kg of millet, 298 kg of rice, 279 kg of maize and 115 kg of sorghum) representing a total average market value of 222,720 FCFA.

Following the definition of Bernard *et al.* (2015), our variable of interest "group membership" is referred to membership of a rural producer organization that provide farmers with farming and farm-related services including access to inputs, markets and credits, collective sales, and capacities reinforcement. Eight type of farmers organizations were mentioned by the surveyed units: the Producers Groups, the Economic Interest Groups, the Rural Associations, the Cooperatives, the Women Producers Groups, the Federations, the Unions, and the Networks. Variable "group membership" is binary, coded as 1 if a member of the household belongs to any of this group, and 0 otherwise. In some households, several family members expressed their belonging to groups, with a maximum of 7 members. However, in 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 households members, are the Economic Interest Groups (43.6%), the Rural Associations (17.3%), the Producers Groups (16.7%), and the Cooperatives (15.3%).

Several control variables have been included in the models, notably the household and its heads socioeconomic characteristics, the households assets, the household access to rural institutions, the ecological conditions, and some environmental risks. Households socioeconomic characteristics variables are sex, age, active household

[5] 1 FCFA=0.0017 USD in December 2019.

size, dependents, education and migrant. Sex is a dummy variable for the gender of the household head, with value 1 for males and 0 otherwise. The households in our sample are predominantly male-headed, with more than 94% of males as heads. Meanwhile, households head age ranges from 16 to 96 years, with an average of 53 years. The household size is a continuous variable that was categorized in 2 groups: active and non-actives members[6]. Average active household size in the sample is around 6 indicating the existence of enough family labor for agricultural tasks. We also include a dummy variable for migration status of the household head. This variable serves as a proxy for involvement in off-farming activities. Education is a binary variable coded as 1 if the farmer has attended at least primary school and 0 if he has no formal education. Most farmers in the sample are not formally educated (more than 60%), they can not read or write. Household assets include equipment and total land area owned. Equipment represents the total value in FCFA of all agricultural implements owned by the household. On average, households in the sample owns about 130,000 FCFA of agricultural implements and about 5.93 hectares of farming land. Variables related to access to infrastructures and institutions include distances to nearest road and access to extension services. Only around 11% of the farmers in our sample have access to extension services. Ecological conditions variables include rainfall, the percentages of clay in soils[7]. Dummy variables for agro-ecological zones are also included due to the expected spatial heterogeneity in farmers conditions to produce food. Most of the households in the analysis are located in the zones of Groundnut, Casamance and South East, gathering more than 88% of farmers in the sample. The included environmental risks variables, faced by the farmer and that could have affected food production during the season, are drought, crop diseases, and the early stop of rain.

4 Results and Discussion

4.1 Comparative Descriptive Analysis

Columns 2, 3 and 4 of table 2 shows the comparative descriptive statistics of the characteristics of producers organizations members and non-members, with the associated p-values of computed differences between means. When comparing farmers groups members to non-members, statistically significant differences can be observed for some of their characteristics. Groups' members tend to have larger households than non-members and they appear to be in average more educated. Groups members have a better access to rural institutions such as extension and subsidies than non-members do. For the cereals production variable, groups members seem to produce more food than non-members and the differences are significant (p-value

[6]First category comprises active members, aged between 15 and 65 years, and second regroups dependents i.e. members aged below 15 years and more than 65 years.

[7]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.

< 0.01). These differences suggest that farmers organizations might play an important role in enhancing farmers' ability to produce more food, and improve locally food security. However, these results cannot allow making inferences about the impact that farmers' groups membership might have on farmers food availability. These comparisons of mean differences do not account for confounding factors such as observed household and farm-level characteristics and unobserved factors (e.g., farmers' innate skills, perception and motivations of membership choice).

4.2 Econometric Estimations

Table 4 presents econometric estimations and columns (1), (2), (3) and (4) refer respectively to OLS model, final step of the 2SLS-IV model, SEM specification, and SEM-IV model. After the results are presented, they are compared and discussed in a separate section.

OLS regression show a relatively high adjusted R^2 of 0.174 and the computed root mean square errors (RMSE) is also low compared to the food availability values (1.026 compared to the mean of 12.313). The estimated coefficient of our variable of interest, i.e., group membership, are positive and significantly different from 0. Estimates show that group membership improve farm households cereals production by 18.7%. This would mean that when one control for the observed characteristics of farmers, being a member of a farmer organization affect positively and significantly the quantity of food available for the farm household.

Results of our IV model exhibit a F test for weak instrument significant, suggesting that the predicted probabilities obtained from the first step are sufficiently strong instruments, corroborating previous justifications of the used instruments (i.e solar grids use and the need for extension services). In addition, the Wu-Hausman test reports a F-statistic = 12.03 with an associated a p-value <0.01, indicating that IV model results are more consistent than OLS, and supporting the use of instrumental variables technique. If we assume that IV estimation techniques are unbiased, the coefficient of our variable of interest can be interpreted as the local average treatment effect. The IV estimates show that the coefficient of group membership exhibits a positive and statistically significant value at 1%, indicating that membership in a producer organization has a strong and positive effect of 28.5% on households' ability to produce cereals, when one controls for bias stemming from households observable and unobservable characteristics. These results support those obtained from OLS.

As stated previously, before implementing the spatial models, we computed two spatial autocorrelation tests. Table 1 shows that the Moran's I statistic, is positive and highly significant ($p < 0.01$), indicating that there is a strong positive spatial correlation between farmers cereals production. Farmers with relatively high food availability seem to live close to other farmers with high level of food production, and households with relatively low food production also tend to live near households with low food availability. These results suggest that spatial auto-correlation should be considered in our analysis. Furthermore, using residuals from OLS estimates, we computed the standard Lagrange Multiplier error test (Anselin, 1988) The null hypothesis was rejected at $p < 0.01$, indicating that at least spatial auto-correlation should be incorporated in our models.

Table 1: Moran I and Lagrange Multiplier tests

	Cereals production
Moran I	0.240^{***}
Standard LM Error	602.9^{***}

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

Column 3 of table 4 presents results from the SEM model. The likelihood ratio test statistic of 527.214 is significant at 1%, suggesting that the spatial error model fit better than a simple linear model. In addition, the Akaike Infomation Criterion (AIC) value of 10877.855 obtained for the spatial error model is lower than that of the linear model (11403.063), indicating a better model fitting for the SEM model. The spatial lag error coefficient λ is positive, significantly different from 0 and with a high value of 0.599, suggesting a high spatial correlation between farmers levels of cereals production. This means that there is a high spatial heterogeneity in food production, due to spatial observable and unobservable characteristics. Furthermore, the variable of group membership shows a positive sign and significantly different from 0 at 1% level. These results suggest that, when one controls for spatial heterogeneity, that is, the played role of geography in Senegalese food availability, belonging to rural producer organization influences significantly and positively the farmer ability to produce food, with an increase of 18 percentage points.

Concerning the SEM-IV model, results show that the spatial lag error coefficient λ is positive and statistically significant at 1% level, with a relative high value of 0.630, showing once again the high spatial heterogeneity in households food availability outcome. Farmers organizations membership also exhibits positive and statistically significant coefficient at 5% level. These results would indicate that, when controlling for spatial heterogeneity and selection bias, farmers organization membership influences significantly and positively the household food availability by 19%. We called this estimated value the "spatial local average treatment", similarly to the standard local average treatment.

Beside the membership in a farmers organization, through all models specifications, other explanatory variables were also significantly associated with the food availability outcome. The other factors that affect significantly cereals production comprise the gender of household head, the number of active household members, the owned assets, the access to extension services and to fertilizer subsidies, the level of rainfall, the south-east agro-ecological zone, and the early stop of rain.

4.3 Discussion

The different results obtained with the various estimation techniques indicate that belonging to a producer or farmer organization increases in general the farm level of food availability. If we consider that food availability and especially domestic food production is an important factor in fighting food insecurity, therefore, our estimates suggest that farmers organizations are effective at improving farm households food security. Similar results were observed in Ethiopia by Zeweld *et al.* (2015) who used the total expenditure per adult equivalent as a proxy for household food security level and Heckman selection model. Our findings also support the recent results in the growing literature on farmer-based organizations in developing countries, where most scholars observed a positive correlation between farmers groups membership and farms performances (Verhofstadt and Maertens, 2014) and farm households economic welfare (Ma and Abdulai, 2016).

The good performances of farmers groups members in Senegal could be explained first by the differential impact of adoption of agricultural technologies such as fertilizers. Our comparative t test analysis show significant differences between members and non-members, in the different subsidies received by farmers (seeds and fertilizers). Subsidies in general improve and encourage the use and intensity of technologies, and therefore enhance farm productions and households food security. In addition, the fertilizer subsidies variable are positively and significantly correlated with cereals productions in all regressions. As shown by Abebaw and Haile (2013), membership in farmers organizations such as cooperatives affects positively the use of technologies (e.g. fertilizer). Adoption of fertilizers is also induced by the differential ease that members of organizations might have to access them, because of being member. Ajah (2015) when analyzing farms access to production inputs in Nigeria observed that in general farmers-based organizations members have significantly a better access to farm inputs than non-members. Furthermore, previous studies have also shown that membership in farmers organization is motivated by the reduction of transaction costs and therefore improving the access of members to farms inputs and technologies compared to non-members.

Earlier, we argued about the importance of the differential effects of rural infrastructure and institutions. The performance of farmers organizations could also be explained by the disparate access to extension services (significant at $p < 0.01$). Farmers groups members tend to have a better access to extension and therefore they are more prone to have access to necessary knowledge and new technologies to increase farm productivity and food productions. In addition, through the social networks within organizations members can diffuse and receive these knowledge and enhance therefore their level of food productions.

Regarding the other drivers of households cereals production, male-headed households seem to produce more food. A plausible interpretation would be that in rural areas male-headed households compared to female-headed, are more likely to have a better access to production inputs (such as labor and secured land) and agricultural modern technologies, therefore they are able to produce more food crops. The owned assets also play an important role in ensuring food production, farmers who have more assets are generally more capable of producing more food crops. We also observed that the relationship between rainfall and the cereals productions exhibits an inverted U-shape behavior, suggesting that farm households food security in Senegal are sensitive to rainfall. Being in the South-east zone also improve food crops production. South-East is the predilection zone of cereals production in Senegal. Farmers living in that area are therefore more prone to produce efficiently and sufficiently cereals and other food crops. Meanwhile the early stop of rain impedes significantly food production in Senegal, backing the previous finding regarding the annual rainfall.

Furthermore, our results showed that farmers cereals productions are affected by the location spatial features. Although, the regressions tried to incorporate most of geographic and physical variables that are observable, the estimated spatial correlation coefficients are still high, denoting the presence of unobserved and unobservable spatial characteristics that seriously affect Senegalese households food availability. The non inclusion of such a strong spatiality into regressions would have led to overestimated coefficients.

5 Concluding Remarks

Producers organizations can constitute main vehicle for access to farms inputs and therefore enhance farm productivity and farms household food production. However, despite the growing literature on collective action groups importance in developing countries, no quantitative studies on the impact of Senegalese farmers organizations has been done. This paper aimed to fill the gap and contribute to literature by applying various estimations techniques including a spatial econometric approach, on a country scale survey data, to derive quantitative effects of membership in farmers organizations on household food availability.

Estimations results revealed that farmers organizations membership affect significantly and strongly farm households cereals production. In addition, results show that households food crops production is also positively and significantly correlated with the households characteristics (gender of the head, active and dependents members, the possession of agricultural assets), the access to extension services and to fertilizers subsidies, and the early stop of rainfall. These results were robust to changes in estimations techniques. Furthermore, farmers food production is also driven by spatial features. These findings support the idea that rural producer organizations have the potential to benefit rural households food security levels by providing conditions and the necessary social networks for the access to technologies, knowledge and production inputs.

Future research should investigate the geographic distribution of farmers organizations and its impacts on farm households performances. In addition, as demonstrated, members performs better compared to non-members, however their efficiency is questionable in regard to the high level of production inputs use. Further analysis are then necessary to derive the effects of membership on members technical efficiency.

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6 Appendix

Table 2: Description of variables

Variables	Description and measurement	Pooled (1)	Members (2)	Non-Members (3)	P-values (4)
Groups Membership	Membership in farmers groups (1=yes, 0=no)				
Cereals production	Cereals production (1.000 FCFA)	222.72 (416.80)	415.82 (1112.27)	203.71 (255.59)	<0.01
	Cereals Productions				
Cereals	Cereals Production (Kg)	1315.60 (2991.97)	2852.84 (8770.41)	1164.28 (1423.09)	<0.01
Millet	Millet Production (Kg)	622.37 (1005.91)	436.44 (874.42)	640.67 (1016.21)	<0.01
Maize	Maize Production (Kg)	279.96 (740.76)	425.21 (1144.43)	265.66 (686.93)	0.01
Rice	Rice Production (Kg)	298.23 (2705.96)	1800.20 (8756.23)	150.38 (520.68)	<0.01
Sorghum	Sorghum Production (Kg)	115.04 (431.55)	190.99 (588.21)	107.57 (412.29)	0.01
	Household and Head characteristics				
Sex	Household head is a male (1=yes, 0=no)	0.94 (0.24)	0.95 (0.23)	0.94 (0.25)	0.40
Age	Age of household head (years)	53.00 (13.47)	51.03 (12.24)	53.19 (13.57)	<0.01
Education	Formal education (1=yes, 0=no)	0.37 (0.48)	0.51 (0.50)	0.35 (0.48)	<0.01
Active members	Active family members	6.10 (3.31)	6.72 (3.57)	6.04 (3.27)	<0.01
Children	Children in the family	4.02 (3.25)	4.82 (3.86)	3.94 (3.18)	<0.01
Migrant	Household head is a migrant (1=yes, 0=no)	0.23 (0.70)	0.26 (0.72)	0.23 (0.70)	0.38
	Household Assets				
Equipment	Agricultural Equipment (1.000.000 FCFA)	0.13 (0.58)	0.18 (0.48)	0.13 (0.58)	0.05
Area Owned	Land size owned by household (ha)	5.93 (8.46)	5.78 (6.33)	5.94 (8.64)	0.65
	Access to infrastructures				
Distance to road	Distance to nearest all-weather road (km)	10.41 (14.57)	10.76 (14.16)	10.38 (14.61)	0.63
Extension	Access to extension services (1=yes, 0=no)	0.11 (0.31)	0.45 (0.50)	0.07 (0.26)	<0.01
Seeds subsides	Access to subsided seeds	0.39 (0.49)	0.47 (0.50)	0.39 (0.49)	<0.01
Fertilizers subsides	Access to subsided Fertilizers	0.33 (0.47)	0.63 (0.48)	0.30 (0.46)	<0.01
	Agro-ecological zones				
Groundnut AEZ	Groundnut agro-ecological zone (1=yes, 0=no)	0.49 (0.50)	0.29 (0.45)	0.51 (0.50)	<0.01
Casamance AEZ	Casamance agro-ecological zone (1=yes, 0=no)	0.27 (0.44)	0.33 (0.47)	0.26 (0.44)	0.02
South-East AEZ	South East agro-ecological zone (1=yes, 0=no)	0.12 (0.32)	0.16 (0.36)	0.11 (0.32)	0.03
Other AEZ	Other agro-ecological zones (1=yes, 0=no)	0.12 (0.32)	0.16 (0.36)	0.11 (0.32)	0.03
	Ecological conditions				
Rainfall	Rainfall 2016 (m)	0.70 (0.29)	0.70 (0.35)	0.70 (0.28)	0.65
Clay	Percentage of clay (%)	20.23 (7.21)	23.65 (5.81)	19.90 (7.24)	<0.01
Drought	Drought (1=yes, 0=no)	0.08 (0.27)	0.07 (0.26)	0.08 (0.27)	0.56
Early Rain Stop	Early rain stop (1=yes, 0=no)	0.37 (0.48)	0.37 (0.48)	0.37 (0.48)	0.74
Crop disease	Crop disease (1=yes, 0=no)	0.07 (0.26)	0.07 (0.25)	0.07 (0.26)	0.72
	Instrumental Variables				
Solar grids	Use of solar grids as lightening (1=yes, 0=no)	0.10 (0.30)	0.15 (0.35)	0.10 (0.30)	0.01
Extension needs	Express need for support (1=yes, 0=no)	0.17 (0.38)	0.14 (0.35)	0.17 (0.38)	0.15
N	Number of Observations	3939	353	3586	3939

Table 3: Instruments Checking

Dependent Variable	Group Membership (1)	Extension (2)	Cereals Productions (3)
Group Membership		1.050 (0.084)***	0.187 (0.064)***
Intercept	−1.182 (0.559)**	−1.663 (0.519)***	10.625 (0.278)***
Sex	−0.113 (0.140)	0.093 (0.128)	0.358 (0.068)***
Age	0.010 (0.017)	0.029 (0.016)*	−0.005 (0.008)
Age squared	−0.000 (0.000)	−0.000 (0.000)	0.000 (0.000)
Education	0.317 (0.068)***	0.120 (0.064)*	−0.007 (0.036)
Active members	0.031 (0.011)***	−0.013 (0.011)	0.038 (0.006)***
Dependents	0.032 (0.010)***	−0.009 (0.010)	0.007 (0.006)
Migrant	0.005 (0.092)	0.298 (0.080)***	−0.125 (0.048)***
Equipment	−0.048 (0.047)	0.075 (0.038)**	0.101 (0.029)***
Area owned	0.003 (0.004)	0.002 (0.004)	0.031 (0.002)***
Distance to road	−0.009 (0.003)***	−0.009 (0.003)***	−0.002 (0.001)
Extension	0.995 (0.081)***		0.367 (0.059)***
Seeds subsidies	0.069 (0.083)	0.036 (0.076)	−0.028 (0.041)
Fertilizers subsidies	0.487 (0.079)***	0.333 (0.074)***	0.321 (0.042)***
Clay	0.044 (0.008)***	0.039 (0.007)***	0.009 (0.004)**
Rainfall	−4.312 (0.836)***	−4.693 (0.748)***	0.521 (0.453)
Rainfall squared	1.802 (0.443)***	2.432 (0.397)***	−0.740 (0.244)***
Groundnut AEZ	−0.083 (0.173)	−0.106 (0.146)	0.187 (0.082)**
Casamance AEZ	0.651 (0.231)***	0.054 (0.201)	0.280 (0.112)**
South-East AEZ	0.358 (0.216)*	0.339 (0.185)*	0.540 (0.106)***
Drought	−0.011 (0.122)	0.220 (0.105)**	0.020 (0.062)
Early rain stop	−0.048 (0.073)	0.343 (0.066)***	−0.119 (0.036)***
Crop diseases	−0.240 (0.133)*	0.100 (0.115)	−0.072 (0.065)
Solar grids	0.280 (0.098)***		0.030 (0.056)
Extension Need		0.323 (0.076)***	0.043 (0.045)
AIC	1849.489	2177.603	
Log Likelihood	-900.745	-1064.801	
Adj. R^2			0.174
RMSE			1.026
N	3939	3939	3939

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

Table 4: Models Estimations: Cereals Productions

	OLS (1)	2SLS-IV (2)	SEM (3)	SEM-IV (4)
Intercept	10.643 (0.277)***	10.576 (0.277)***	10.216 (0.305)***	10.195(0.331)***
Group Membership	0.187 (0.064)***	0.285 (0.072)***	0.180 (0.061)***	0.19(0.074)**
Sex	0.357 (0.068)***	0.356 (0.068)***	0.252 (0.063)***	0.254(0.066)***
Age	−0.005 (0.008)	−0.005 (0.008)	−0.002 (0.007)	−0.002(0.007)
Age squared	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000(0.000)
Education	−0.006 (0.036)	−0.013 (0.036)	0.006 (0.035)	0.002(0.035)
Active members	0.038 (0.006)***	0.037 (0.006)***	0.046 (0.005)***	0.046(0.007)***
Dependents	0.007 (0.006)	0.007 (0.006)	0.011 (0.005)**	0.011(0.005)**
Migrant	−0.121 (0.048)**	−0.127 (0.048)***	−0.020 (0.045)	−0.028(0.045)
Equipment	0.102 (0.029)***	0.100 (0.029)***	0.066 (0.026)**	0.066(0.026)**
Area owned	0.031 (0.002)***	0.031 (0.002)***	0.029 (0.002)***	0.029(0.007)***
Distance to road	−0.002 (0.001)	−0.002 (0.001)	−0.002 (0.002)	−0.001(0.002)
Extension	0.370 (0.058)***	0.461 (0.070)***	0.233 (0.058)***	0.354(0.07)***
Seeds subsidies	−0.027 (0.041)	−0.027 (0.041)	0.050 (0.040)	0.046(0.038)
Fertilizers subsidies	0.321 (0.042)***	0.301 (0.043)***	0.209 (0.042)***	0.203(0.04)***
Clay	0.009 (0.004)**	0.007 (0.004)*	0.006 (0.005)	0.005(0.006)
Rainfall	0.510 (0.452)	0.785 (0.456)*	1.516 (0.651)**	1.63(0.743)**
Rainfall squared	−0.736 (0.244)***	−0.867 (0.246)***	−1.192 (0.352)***	−1.252(0.403)***
Groundnut AEZ	0.185 (0.082)**	0.189 (0.082)**	0.162 (0.105)	0.164(0.125)
Casamance AEZ	0.281 (0.112)**	0.263 (0.112)**	0.228 (0.148)	0.222(0.162)
South-East AEZ	0.537 (0.105)***	0.522 (0.106)***	0.448 (0.144)***	0.443(0.152)***
Drought	0.019 (0.062)	0.020 (0.062)	0.057 (0.061)	0.056(0.06)
Early rain stop	−0.120 (0.036)***	−0.123 (0.036)***	−0.064 (0.037)*	−0.07(0.037)*
Crop diseases	−0.073 (0.065)	−0.071 (0.065)	−0.106 (0.064)	−0.106(0.064)*
λ (Spatial error lag)			0.599 (0.023)***	0.630(0.027)***
Adj. R^2	0.174	0.173		
RMSE	1.026	1.026		
LR test			527.214***	
AIC	11403.069		10877.855	
Weak Instruments (Group membership)		7641.24***		
Weak Instruments (Extension)		4797.36***		
Wu-Hausman test		12.030***		
N	3939	3939	3939	3939

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