Journal of Agriculture and Environmental Sciences
December 2018, Vol. 7, No. 2, pp. 90-100
ISSN 2334-2404(Print) 2334-2412(Online)

Published by American Research Institute for Policy Development
DOI: 10.15640/jns.v7n2a10
URL: https://doi.org/10.15640/jns.v7n2a10

Impact of Adoption of Improved Pearl Millet Varieties on Productivity in Central Senegal

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Abstract

Agricultural innovations are important for increasing productivity and revenues of rural households. Investments are made in agricultural research to generate improved varieties as well as new techniques in main crops. Our paper uses plot and household level data of pearl millet producers to assess impact of adoption of improved pearl millet varieties on productivity. Pearl millet is the most cultivated staple crop in the country and is the main component in rural as well as urban households' diet The paper uses propensity score matching and endogenous switching regression analysis to control observed as well as unobserved heterogeneity. Results show that adoption of improved pearl millet varieties has a positive impact on yields. They also show a negative selection in adoption, meaning that least productive producers are using improved varieties. Overall, results indicate that in order to achieve food security, investments are needed to increase adoption and promote good practices in using improved pearl millet varieties.

Key words: pearl millet, impact, PSM, ESR, improved seeds, adoption

JEL codes: Q16, O13, C10

I. Introduction

As in many west African countries, agriculture is the main source of income for rural households in Senegal. However, despite its importance in the national economy, the agricultural sector faces many constraints which are, among others, erratic rainfall, low and unattractive prices, low potential for irrigation, pest attacks, post harvest losses, non-compliance with good agricultural practices and low rate of technologies and innovations adoption by farmers (Muzari et al., 2012). Thus, the challenge of food security for a growing population has motivated national authorities to invest in agricultural research in order to increase productivity. Agricultural innovations are important for increasing yields and revenues of rural households. In 2014, the Senegalese government has launched a new program to increase availability of certified improved seeds and, in the context of the West Africa Agricultural Productivity Program (WAAPP), new varieties have been generated and disseminated, particularly for pearl millet and sorghum. Therefore, efforts are constantly being made to promote the use of improved varieties by producers. Given the growth of investments in research, increasing attention is being paid to the contribution of these investments towards the achievement of development goals.

This paper focuses on the adoption of improved pearl millet varieties in Senegal. Pearl millet is the most cultivated staple crop in the country and is the main component in rural as well as urban households' diet. It is mostly cultivated in Central Senegal and, in 2017, it represented 55% of cereal cultivated areas. National average pearl millet yields have increased from 519 kg/ha in 1997 to 930 kg/ha in 2017. In order to increase aggregate millet production, agricultural research has released more than 10 improved pearl millet varieties. However, empirical evidence on rates of adoption and impact of improved varieties on yields and welfare in Senegal is not well documented.

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Previous research on adoption of agricultural innovations has shown a positive impact of these on yields, incomes and poverty reduction (Mendola, 2007; Duflo et al., 2008; Kassie et al., 2011; Mulhubran et al., 2012; Shiferaw et al., 2014; Kabunga et al., 2014; Awotide et al., 2015; Zeng et al., 2015; Abdoulaye et al., 2018). Most of these studies are focused in East Africa. For example, Mulhubran et al. (2012) showed, by using a sample of Tanzanian farmers, that those who adopt improved maize and pigeonpea varieties have an income of 30-33% higher than that of producers who use traditional varieties. Kassie *et al.* (2011) also highlighted the positive impact of improved peanut varieties on net income and poverty reduction in Uganda. In order to design policies that address low yields obtained by pearl millet producers in Senegal, it is necessary to identify main adoption factors as well as impact of adoption.

This paper's objective is to assess the impact of adoption of improved pearl millet varieties in Central Senegal. Impact will be assessed on productivity. The paper contributes to the existing literature by being the first one to work on this subject in Senegal. In addition, we use impact assessment methods to take into account both observed and unobserved heterogeneity, and to check robustness of results. The restof the paper is structured as follows: section two presents methodology and data; section three presents results and discussion; section five concludes.

II. Data and methodology

II.1. Data sources description

Data used in this paper come from surveys conducted by the Senegalese Institute of Agricultural Research between May and August 2014, in the regions of Kaffrine and Thies. The survey's objective was to collect data that will be used in order to identify factors of adoption of improved pearl millet varieties and assess the impact of adoption on yields. Surveys targeted cereal producers, but also key informants such as village chiefs, members of farmers 'organizations and agricultural technicians. Database is composed of 532 producers randomly selected, among which 445 pearl millet producers. Women represented 26% of the sample.

During the survey, information was collected on producer's characteristics (age, sex, schooling level, size of household, etc.), crops cultivated and inputs used, knowledge and use of improved varieties, income sources, food and nonfood expenditures. Outcome variable, productivity, is obtained by dividing total production by milletsownarea. Treatment variable, adoption of improved millet seeds, was measured using different questions. First the producer was asked if he (she) used an improved millet variety during the 2013 and 2012 rainy seasons; if yes, the source of the improved seed was asked and whether seeds were certified or not. Crossing both information, we considered that a producer is an adopter if he stated that he used improved varieties in 2012 and 2013, that seeds were certified and did not come from previous harvests.

Data showed that adopters did not grow a wide diversity of varieties, 91% of them grew Souna 3, a variety created in 1969 and very popular among Senegalese millet producers. Other observed improved varieties are IBV 8004 and IBV 8001.

II.2. Methodology

Two methods will be used to measure impact of improved millet varieties on yields. First, we assume that there is a group of producers (called the control group) that shares the same pretreatment characteristics than adopters. Under this assumption, the propensity score matching method will be used to assess impact of adoption on yields. However, hypothesis of selection on observables is unlikely in practice (Alene et Manyong, 2007; Abdulai et Huffman, 2014). Then] we will relax this assumption and use the endogenous switching regression model.

II.1. Theoretical framework

II.1.1. Propensity Score Matching (PSM)

The PSM method was pioneered by Rubin (1973) whose work was followed by those of Rosenbaum and Rubin (1983, 1984, 1985). It consists in comparing the results of a treatment group (adopters) to a control group (non-adopters); a comparison based on matching according to their previous characteristics that could be related to adoption. These characteristics are in the vector of explanatory variables, denoted X. This vector is composed of n variables $x_j, j = 1, \ldots\ldots, n$ and takes the value X_i for each individual i. Treatment is represented by variable D which takes the value 1 if the producer adopts improved pearl millet varieties and 0 otherwise. We denote Y_{i1} the outcome with treatment and Y_{i0} the outcome without treatment.

A rational producer adopts improved seeds only if the gain is positive, that is when $Y_{i1}>Y_{i0}$. To use PSM, we assume that adoption of improved varieties is related to the vector of explanatory variables X. Matching exploits the idea that adoption, corrected of the effect of X, can be considered as random. This gives the Conditional Independence Assumption defined as follows:

$$Y_{i1,}Y_{i0} \perp D_i \mid X_i$$

One strategy could be to match treated and untreated units along each value of variable x_j ;but this would create a dimensional problem because these variables have multiple values. To address this difficulty, Rosenbaum and Rubin (1983a, 1984) have established the following theorem :

Theorem 1: Let $p(X_i)$ be the probability of receiving the treatment for individual i given the vector of variables$X$, defined by $p(X_i) = Prob[D_i = 1|X_i]$, then

$$Y_{i1,}Y_{i0} \perp D_i \mid X_i \rightarrow Y_{i1,}Y_{i0} \perp D_i \mid p(X_i)$$

This theorem reduces the size of the problem by stating that if the outcome is independent of treatment, conditional on the vector X_i, then it is also independent of treatment conditional on the probability$p(X_i)$, called propensity score.

Therefore, conditioning with respect to $p(X_i)$, treatment is considered random.

If $Y_{i0} \perp D_i \mid p(X_i)$,then:

$$E[Y_{i0} \mid D_i = 0, p(X_i)] = E[Y_{i0} \mid D_i = 1, p(X_i)] = E[(Y_{i0}, p(X_i))] \quad (1)$$

Equation 1 is the identifying condition. Given p(X), the PSM estimator $\alpha$is :

$$\begin{aligned}\alpha_{PSMp\,(X)} &= E[Y_{i1} \mid D_i = 1, p(X_i)] - E[Y_{i0} \mid D_i = 0, p(X_i)] \\ &= E[Y_{i1} \mid D_i = 1, p(X_i)] - E[Y_{i0} \mid D_i = 1, p(X_i)] \\ &= \alpha_{ATT\,,p\,(X)}\end{aligned}$$

This is the Average Treatment effect on the Treated (ATT) conditional on p(X).

Another requirement of the PSM method is the common support condition (Dehejia and Wahba, 1999; Caliendo and Kopeinig, 2008) which is:

$$0 < p(X_i) < 1 \quad (2)$$

Under condition (2), the non conditional PSM estimator can be computed as follows:

$$\alpha_{PSM} = E_{p(X_i)\,\mid D_i=1}\big[E[Y_{i1} \mid D_i = 1, p(X_i)] - E[Y_{i0} \mid D_i = 1, p(X_i)]\big] = \alpha_{ATT} \quad (3)$$

II.1.2. The endogenous switching regression model

The issue of endogeneity in technology adoption results from the fact that adoption is voluntary (self-selection) or some technologies are intended for targeted groups (Alene et Manyong, 2007). Producers choose to adopt the technology by taking into account (among other factors) the benefit they can derive from it, represented here by yields. Beyond observable factors, unobservable variables such as skill levels, agricultural practices, information asymmetries, transaction costs etc. can determine both adoption and yields. This justifies the choice of using the endogenous switching regression model (ESR), developed by Lee (1978) who has generalized the Heckman correction model (Heckman, 1976). It takes into account selection on unobservable to measure the impact of adoption of improved pearl millet varieties on yields.

The ESR model has two main parts:

1. A probit model to identify determinants of adoption of improved varieties;
2. Two functions of yields, one for adopters and one for non-adopters.

Returns from adoption can be represented for each rational producer i by the latent variableD_i^*. The latter is not observed but it is a function of observable characteristics Z influencing adoption. Thus,

$$\begin{cases} D_i^{\,*} = \alpha Z + \varepsilon_i \\ D_i = 1 \text{ if} D_i^{\,*} > 0 (3) \\ D_i = 0 \text{ otherwise} \end{cases}$$

The vector Z includes variables from the probit model that are potentially related to adoption such as acreage, human capital, access to credit and other socioeconomic variables characterizing the producer and his farm.

The error term ε with mean 0 and variance σ_ε^2 represents measurement errors and variables known by the producer but unobserved by the researcher (Abdulai et Huffman, 2014).

In the model, yields are specified for adopters and non-adopters. Noting Y_{i1} yields of adopters, Y_{i0} yields of non-adopters, T the adoption status, W plot characteristics determining yields and Xhousehold characteristics determining yields, equations are written as follows for each producer i,

$$Y_{i1} = f(T, W, X, \beta_1) + u_{i1} \text{if} D_i = 1 \quad (4)$$
$$Y_{i0} = f(W, X, \beta_0) + u_{i0} \text{if} D_i = 0 \quad (5)$$

As shown earlier, producer adopts improved variety only if the gain is positive, that is when $Y_{i1}>Y_{i0}$.
Error termsε, u_1 and u_0 have a trivariate normal distribution with mean vector 0 and a variance-covariance matrix written as :

$$\Omega = \begin{bmatrix} \sigma_\varepsilon^2 & \sigma_{\varepsilon u_1} & \sigma_{\varepsilon u_0} \\ \sigma_{\varepsilon u_1} & \sigma_{u_1}^2 & \sigma_{u_1 u_0} \\ \sigma_{\varepsilon u_0} & \sigma_{u_1 u_0} & \sigma_{u_0}^2 \end{bmatrix}$$

With $var(\varepsilon) = \sigma_\varepsilon^2$, $var(u_1) = \sigma_{u_1}^2$, $var(u_0) = \sigma_{u_0}^2$, $cov(\varepsilon, u_1) = \sigma_{\varepsilon u_1}$, $cov(\varepsilon, u_0) = \sigma_{\varepsilon u_0}$, $cov(u_1, u_0) = \sigma_{u_1 u_0}$. By convention, it is generally admitted that$\sigma_\varepsilon^2 = 1$, because α is estimated up to a scalar (Maddala, 1983, Lokshin et Sajaia, 2004 ; Alene et Manyong, 2005).

Selection bias is modelled by a relationship between the choice equation (latent variable) and the yield equation. This relationship is expressed by$corr(\varepsilon, u) = \rho$. ESR addresses selection bias by estimating the inverse Mills ratios (λ_{i1} and λ_{i1}) and the covariance terms ($\sigma_{\varepsilon u_1}$, $\sigma_{\varepsilon u_0}$) and including them as auxiliary regressors in equations (4) and (5) (Abdoulaye et al., 2017). Absence of selection bias is rejected if$\sigma_{\varepsilon u_1}$ and $\sigma_{\varepsilon u_0}$are significant:

The ESR model estimates can be used to estimate ATT (Average Treatment Effect on Treated producers) as follows:

$$\begin{aligned} ATT &= E[Y_{i1} \mid D_i = 1] - E[Y_{i0} \mid D_i = 1] \\ &= f(T, W, X, \beta_1) + \lambda_{i1}\sigma_{\varepsilon u_1} - (f(W, X, \beta_0) + \lambda_{i0}\sigma_{\varepsilon u_0}) \end{aligned} \quad (6)$$

II.2. Empirical Specification

Propensity scores will be estimated with the logit model. Two methods will be used for matching: the nearest neighbor (choice of 5 neighbors) with replacement and kernel method. We tested other methods but that of the nearest neighbor produced the best results in terms of matching quality.In the ESR model, selection of variables to include in vectors Z, W and X are important. Indeed, for the model to be identified there must be at least one variable of Z which is not in W and X. This variable can be regarded as an instrument determining adoption of improved varieties. Following Suri's example (2011) who had taken the distance from a fertilizer supplier as an instrument, the existence of a fertilizer supplier in the village is included in Z vector but not in in W and X. Existence of a fertilizer supplier in the village should be correlated to adoption of improved varieties in the sense that those who sell fertilizers used to sell improved varieties seeds. The second instrument is the contact with an NGO. NGOs give producers access to improved varieties because they are in touch with agricultural research agents. Both instruments can be considered exogenous once the amounts of fertilizers are taken into account in the model as well as other variables that may result from contact with an NGO like access to credit and agricultural training.

The ESR can be estimated in two steps. The first step is estimation of the probit model of determinants of adoption. In the second step, the estimated probabilities will allow the calculation of inverse Mills ratios λ_{i1} and λ_{i0}. However, according to Lokshin and Sajaia (2004), this two-stage estimation is inefficient because standard errors are not consistent. They recommend to use Full Information Maximum Likelihood Method (FIML) that simultaneously estimates the probit model and both yield equations. We follow their recommendation and use the FIML to estimate the ESR model. Descriptive statistics of variables included in both impact assessment methods are presented in Table 1 and Table 2.

Table 1: Descriptive statistics of the PSM model variables

Name	Description	Yes (%)	Observations
certifmil	Adoption of improved pearl millet varities	12.4	445
cont_ong	Contact with an NGO	6.5	445
sexe	Sex of producer	26 (women)	445
usage_engrais	Use of chemicalfertilizers	31.6	445
formation1	Arabiceducation	57	445
formation2	Primary and/or secondary school	10.5	445
f_agricole	Agricultural training/internship	6.5	445
cont_op	Membership in a producer organization	20	445
obtention_credit	Received a financial loan	24	445
koungheul	Department of Koungheul	64.5	445
mbour	Department of Mbour	12.8	445
thies	Department of Thiès	7.4	445

Source : Authors' calculations

Table 2: Descriptive statistics of the ESR model variables

Discrete variables				
Name	**Description**	**Yes (%)**	**Observations**	
cont_ong	Contact with an NGO	6.5	445	
sexe	Sex of producer	26	445	
usage_engrais	Use of chemicalfertilizers	31.6	445	
formation1	Arabiceducation	57	445	
formation2	Primary and/or secondary school	10.5	445	
f_agricole	Agricultural training/internship	6.5	445	
cont_op	Membership in producerorganization	20	445	
obtention_credit	Received a financial loan	24	445	
Koungheul	Department of Koungheul	64.5	445	
Mbour	Department of Mbour	12.8	445	
Thies	Department of Thiès	7.4	445	
vendeur_fert	Presence of a fertilizersupplier in the village	6.5	445	
revenus_nonagri	Non agricultural revenues	62.25	445	
Continuous variables				
Nom	**Description**	**Mean**	**Standard deviation**	**Observations**
lrend_mil (dependant variable)	*Logarithm of pearl millet yield*	*6*	*0.6*	*445*
sup_cer	Area sown to cereals (ha)	3	3.1	445
age	Age of the producer (years)	48	14.7	445
NPK_hect	Quantity of NPK fertilizer per hectare (kg/ha)	31	66.9	445
uree_hect	Quantity of urea fertilizer per hectare (kg/ha)	2	12.5	445
sem_hect	Quantity of seeds per hectare	4	1.3	445
mofam_hect	Size of family workforce per hectare	2	2.1	445
nbrmat_hect	Number of agricultural machines per hectare	1	1	445

Source : Authors' calculations

III. Results and discussions

In this section we present results of the PSM and ESR models.

III.1. PSM model

III.1.1. Determinants of adoption

Results of the logit estimation of p-scores are presented in Table 3. Effects of variables use of chemical fertilizers, producer's age, agricultural training/internship, access to credit and membership in producers organizations included in the model are globally significant. As expected, there is a positive association between the use of chemical fertilizers and adoption of improved varieties. Agricultural training also positively affects adoption. Results also show that location fixed effects reduce the probability of adoption in Koungheul while they increase the probability in Mbour and Thies, this with respect to the fourth department, Tivaouane, which is the reference.

Table 3:Results of logit estimation

Certifmil	Coefficient	P>z
formation1	-0.470	0.302
formation2	-0.665	0.266
usage_engrais	1.571***	0.000
sexe	-0.518	0.346
age	-0.0368*	0.016
f_agricole	2.094***	0.000
obtention_credit	1.202*	0.011
cont_op	1.119*	0.025
koungheul	-1.916**	0.005
mbour	1.714*	0.011
thies	1.272	0.083
Number of observations	443.00	
LR chi2(11)	107.40	
Prob>chi2	0.0000	
Pseudo R2	0.3232	

Source : author'scalculations
Significancelevel of * 5%, ** 1%, ***0,1%

III.1.2. Matchingquality

Matching quality has been evaluated along with many criteria, following Rubin (2001), Kassie *et al.* (2011) and Shiferaw*et al.* (2014). Tables 4 and 5 present tests of mean differences before and after matching.

Table 4: Test of mean differences before matching

	Mean		
Variable'sname	**Adopters**	**Non adopters**	**Difference**
formation1	0.4	0.59	-0.15** (0.006)
formation2	0.16	0.09	0.07 (0.139)
usage_engrais	0.62	0.35	0.27*** (0.000)
sexe	0.17	0.27	-0.1 (0.083)
age	51.02	47.58	3.44 (0.104)
f_agricole	0.31	0.031	0.279*** (0.000)
obtention_credit	0.42	0.22	0.2*** (0.001)
cont_op	0.25	0.19	0.06 (0.268)
koungheul	0.31	0.69	-0.38*** (0.000)
mbour	0.36	0.09	0.27*** (0.000)
thies	0.18	0.06	0.12*** (0.001)

Source : author's calculations
Significancelevel of * 5%, ** 1%, ***0,1%
p-values in parentheses

Table 4 highlights significant differences between adopters and non-adopters of improved pearl millet varieties, before matching. First, use of chemical fertilizers differs between groups: 62% of adopters use chemical fertilizers, while they are 35% among non-adopters. Also, adopters are relatively better educated, benefited more from an agricultural training/internship and benefited more from credit in 2013. Location fixed effects are also different between adopters and non-adopters. Compared to Thies residents, those who live in Koungheul adopt less improved pearl millet varieties. These significant differences in means of explanatory variables are assumed to be at the origin of self-selection in adoption.After matching, no significant difference was noted between means of explanatory variables. This guarantees that treated and untreated groups are comparable in terms of observable variables (Table 5).

Table 5: Test of means differences after matching

	Mean		
Variable'sname	**Adopters**	**Non adopters**	**Difference**
formation1	0.43	0.41	0.02 (0.84)
formation2	0.16	0.16	0 (0.96)
usage_engrais	0.57	0.53	0.04 (0.66)
sexe	0.18	0.17	0.01 (0.83)
age	50.06	51.98	-1.92 (0.45)
f_agricole	0.22	0.23	-0.01 (0.92)
obtention_credit	0.37	0.38	-0.01 (0.93)
cont_op	0.27	0.26	0.01 (0.93)
koungheul	0.35	0.29	0.06 (0.52)
mbour	0.31	0.27	0.04 (0.69)
thies	0.20	0.20	0 (0.92)

Source : author's calculations
p-values in parentheses

Figure 1 illustrates the standardized percentage bias after matching; it shows a significant reduction after matching. Before matching, its value is most of the time greater than 10% and the highest value is around 50% for variables such as education, agricultural training and access to credit. After matching, location fixed effects of Mbour and Koungheul, age of producer and the use of chemical fertilizers might still have a standardized bias greater than 5%. But, these are the best results that have been obtained on this sample.

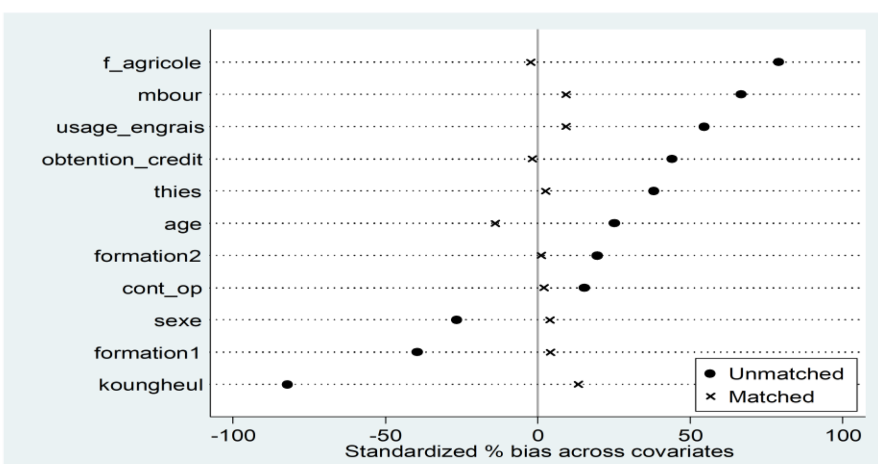

Figure 1: Standardized bias before and after matching

As suggested by Caliendo and Kopeing (2008), table 6 presents other matching quality indicators; these are the LR test, the pseudo-R2 and the mean bias.

Table 6: Other matching quality indicators

Sample	Pseudo R2	LR chi2	p>chi2	Meanbias
Unmatched	0.324	107.82	0.000	44.6
Matched (nearestneighbor)	0.024	3.23	0.987	5.8
Matched (kernel)	0.025	3.41	0.984	8.2

Source : autours calculations

Results indicate a good matching quality of producers of pearl millet. The pseudo-R2 is low after matching, [as well as for the kernel method than for the nearest neighbor method] (2.4% and 2.5%). In addition, maximum likelihood tests are rejected before the matching but not after. The mean bias is also very small compared to the unmatched sample. Final indicator for checking matching quality is the common support condition. It is shown in Figure 2.

Figure 2: Distribution of p-scores over the common support

A significant point on the distribution of propensity scores among producers of pearl millet is its concentration around 0, reflecting the low adoption rate of improved varieties. The common support is however satisfied with a good superposition of probabilities of treated and untreated individuals. There is a loss of six adopters, this is equivalent to 11% of treated or 1.3% of observations.

III.1.3. Impact of adoption on productivity

According to the PSM model, adoption of improved pearl millet varieties has a positive impact on yields (Table 7). Effect is significant at the 5% level; the coefficient is 0.27 with the nearest neighbor method and 0.29 with the kernel method; this means that adoption would increase yields by 31 to 33.6%.

Table 7: Results of the PSM model

Dependant variable	Treated	Controls	ATT	Std-errors	t-stat
Log pearl millet yield (nearest neighbor)	5.88	5.61	0.27*	0.13	2.14
Log pearl millet yield (kernel)	5.88	5.59	0.29*	0.13	2.2

Source : Authors calculations
Significance level of * 5%

III.2. ESR model

Table 8 presents ATE, ATT and the value of the correlation coefficient rho according to the ESR model. Results of the probit estimation and determinants of yields are presented in appendix 1.

Table 8: Results of the ESR model

Type of impact	Value	Standard-errors	t-stat
ATE	0.52***	0.17	3.07
ATT	0.57***	0.16	3.56
Variable	**Coefficient**	**Standard-errors**	**t-stat**
rho	-0.48	0.12***	4

Source : Authors calculations
Significance level of *** 0.1%

Taking into account selection on unobservables, the coefficient of ATE is 0.52 and that of ATT 0.57. In other words, average treatment effect is an increase of 68% in yields while ATT is an increase in yields of 77%. Both effects are significant at the 0.1% level. Compared to the PSM, the results of the ESR model show a higher impact of adoption of improved pearl millet varieties. The negative sign of rho means that unobservable variables that increase yields are correlated with unobservable variables that reduce adoption of improved pearl millet varieties. This means that the least productive individuals are more likely to adopt. In this case, failure to take it into account will lead to an underestimation of the impact of adoption. That is why we obtain a greater effect in the ESR model. Interactions were introduced to check whether there is impact heterogeneity related to gender, access to credit and agricultural training, but the coefficients are not significant.

Our results show the need to continue promoting improved varieties so that they could be adopted by more producers. They are consistent with the literature on impact of adoption of improved varieties (Wu *et al.*, 2010; Abdulai and Huffman, 2014; Khonje*et al.*, 2015. Zeng *et al*, 2015). Ali *et al.* (2015) found that adoption of certified wheat seeds increases yields by 8 to 12 kg per acre. Moreover, adopters have a poverty rate of 6 to 7% lower than non-adopters. The size of the effect we found is important, but it varies depending on the model. Shiferaw*et al.* (2014) also found variation when studying impact of adoption of improved wheat varieties, using the PSM and the ESR models. By increasing yields, improved pearl millet varieties will contribute to reducing food insecurity in rural areas. Food availability will increase and producers can also sell surpluses in order to have more revenues.

IV. Conclusion

Using representative plot and household data from Central Senegal, this study examined the productivity implications of adoption of improved pearl millet varieties. To check robustness of results, two methodologies were used: propensity score matching and endogenous switching regression. Econometric results show that adoption of improved pearl millet varieties has a positive impact on yields. Results vary from one model to another, depending on how we treat the selectivity issue. However, rate of adoption of improved pearl millet varieties is still low (12.5% in our sample), and if adopted producers are far from achieving the full potential of those varieties which can have yields up to two tons per hectare. Thus, knowledge of improved varieties should be promoted and agricultural technologies diffusion agents should focus on training producers on good agricultural practices. Central Senegal is characterized by soil degradation because of many years of exploitation; to ensure high levels of production and food security, access and use of organic fertilizers should be ensured. Having a national policy of soil regeneration is also necessary to make agriculture in this area sustainable.

Acknowledgements:

Authors would like to thank the West African Agricultural Productivity Program for financing this work. Special thanks go to Dr Tahirou Abdoulaye, Dr Mbene Dieye Faye and Mrs Diamilatou Goudiaby Gueye for reviewing this article.

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Appendix 1: Estimation results of the ESR model

Number of observations = 443
Wald chi2 (21) = 196,92
Prob>chi2 (21)=0,0000

Table 9: Estimation results of the ESR model

Variables	**Coefficient**	**Standard errors**	**z**
Dependant variable : logarithm of pearl millet yield			
sup_cer	-0.021*	0.009	-2.34
NPK_hect	0.001	0.001	1.16
uree_hect	0.003	0.002	1.66
sem_hect	0.010	0.027	0.35
mofam_hect	-0.012	0.022	-0.54
nbrmat_hect	0.101**	0.037	2.72
sexe	0.043	0.074	0.58
age	0.006**	0.002	2.57
formation1	-0.027	0.071	-0.39
formation2	-0.161	0.111	-1.45
f_agricole	-0.268	0.178	-1.5
cont_op	0.085	0.075	1.13
obtention_credit	0.027	0.083	0.32
koungheul	0.619***	0.119	5.19
mbour	0.220	0.121	1.82
thies	-0.193	0.130	-1.49
certifmil#			
c,f_agricole			
1	0.005	0.225	0.02
c,obtention_credit			
1	0.040	0.146	0.28
c,NPK_hect			
1	0.002	0.001	1.58
c,sexe			
1	-0.077	0.208	-0.37
certifmil	0.462**	0.171	2.7
_cons	5.067	0.208	24.32
Dependant variable : certifmil			
formation1	-0.418*	0.214	-1.95
formation2	-0.265	0.293	-0.9
f_agricole	1.454***	0.278	5.23
sexe	-0.688**	0.262	-2.63
cont_ong	0.894***	0.284	3.14
vendeur_fert	1.672***	0.254	6.6
obtention_~t	0.730***	0.198	3.69
_cons	-1.454***	0.185	-7.86
/athrho	-0.523	0.154	-3.39
/lnsigma	-0.529	0.038	-14.11
Variable	**Coefficient**	**Coefficient**	**95% confidence interval**
Rho	-0.480***	0.119	[-0.678 ;-0.217]
Sigma	0.589***	0.022	[0.547 ; 0.634]
Lambda	-0.283***	0.076	[-0.431 ;-0.134]
Wald test of indep. Eqns. (rho=0): chi2(1)=11,51 Prob>chi2=0,0007			

Significance level of * 5%, ** 1%, ***0,1%