RESEARCH ARTICLE

Impact of the Adoption of Improved Varieties of Household Income of Farmers in the Department of the Atlantic in Southern Benin

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ABSTRACT

In Benin, maize occupies a strategic place in the agricultural sector due to its growing importance in national consumption and trade with neighboring countries. This study aims to analyze the impact of the adoption of improved maize varieties on the income and expenditure of maize farmers in the South Atlantic Department of Benin. The data used were collected from 144 maize growers in the Atlantic Department. Maize farmers with or without improved varieties were selected randomly. The average treatment effect method with propensity score matching was used to estimate the impact of the adoption of improved maize varieties on household income and expenditure. Maize growers using four impact indicators: (i) Netincome; (ii) school expenses; (iii) health expenditure; and (iv) food expenditures. The results showed that the adoption of improved maize varieties led to an improvement in annual netincome (a relative effect of 8.78%), health expenditure (a relative effect of 15.88%), and expenditure on education (a relative effect of 16.08%). On the other hand, the adoption of improved varieties of maize has no significant influence on the expenditure invested in the dietof household members. It shows that the adoption of improved varieties of maize by which has a positive impact on the netincome, health expenditure, and household education expenditure.

Key words: Adoption varieties, income, household expenditure?

INTRODUCTION

For several decades, three regions have concentrated most of the rate world's poverty: East Asia/Pacific, South Asia, and Sub-Saharan Africa with almost a 95% rate (WB, 2015). In 1990, East Asia counted half of the poor, compared to about 15% in sub-Saharan Africa. By 2015, the situation would have virtually reversed, with sub-Saharan Africa concentrating half of the world's poor, compared with around 12% in East Asia (WB, 2015). Three-quarters of Africa's poor live in rural areas where the primary economic activity is agriculture (IFAD, 2011). Thus, agriculture is the main source of income for 90% of the rural population in Africa (UNECA, 2005, cited by Olomola, 2010). In low-income countries, the agricultural sector employs 60% of the labor force and represents 25% of gross domestic product (GDP).[1]

In Benin, agriculture represents a strategic weight in the social and economic fabric. Above all, Benin's agricultural sector employs about 58% of the labor force and accounts for nearly 36% of GDP and 88% of export earnings (World Statistics, 2012). It is considered as the sector whose many potentialities must be judiciously exploited to support national economic growth and contribute to effectively fight against poverty (APRM, 2013). In the constitution of GDP, cotton cultivation on its own contribute for 80% of official export earnings. The cotton sector alone represents 45% of tax revenues (excluding customs) and contributes in terms of value added for 13% to the formation of

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the national GDP. It is the sector that has benefited from more investments and loan to producers (APRM, 2013 quoted by Sossou, 2015).

However, in Benin, the level of productivity of almost all agricultural crops is below that recorded elsewhere in the world or those allowed by local agro-ecological conditions. Yields of major crops have remained below average yields globally. Thus, for the main cereals such as maize, rice, and sorghum, the average yields in Benin over the past 15 years are, respectively, 1.2 t/ha, 2.4 t/ha, and 0.9 t/ha against yields. Global average is 4 t/ha, 3.5 t/ha, and 2 t/ha for each products (Sossou, 2015). The main causes are soil depletion, climate risks, and variability, and lack of certified seeds, which compromise the cultivation and availability of staples such as cereals. Their agricultural production has, therefore, remained essentially underdeveloped, both for domestic markets and for export.[2] It should be noted that the number of households practicing agriculture has fallen sharply in the past 5 years, currently at 36% against 53% in 2008 (WFP, 2014).

The development and introduction of improved agricultural technologies are one of the most widely used strategies in the world for increasing productivity in the agricultural sector.[3] The ultimate goal of these technologies is to contribute to the improvement of people's living conditions while reducing poverty and food insecurity.

In Africa, the most widely grown cereal is maize and fits into basic diets. For example, 95% of maize produced in sub-Saharan Africa is an important part of daily food (Jensen *et al.*, 2007). In Benin, maize is currently the most consumed cereal, far ahead of rice and sorghum. Indeed, this cereal is integrated into the production systems and the eating habits of the whole population of Benin but to varying degrees. Maize now ranks first in the national food system. It is the main staple food of all the southern part of Benin, being 2/3 of the national population (Sodjinou *et al.*, 2007).

To improve the agricultural productivity of maize, improved varieties resistant to parasitic attacks, short cycle, and high yields have been developed and introduced in rural areas by the National Institute of Agronomy Research in Benin services and those of the Regional Centers for Agricultural Promotion with the support of some development projects implemented by the international institute of tropical agriculture (IITA). According to Adégbola and Agboh-Noameshie,[4] it was found

that 99% of informed producers, respectively, grew at least one improved variety of maize in 2009. The average number of improved varieties grown by producers in 2009 is about three and this number may go up to 12 for some producers. However, the impact of adopting these varieties has not been addressed. However, the technical performance of a technology is not enough to demonstrate its impact on the performance of adopters (Honlonkou, 1999) and their well-being. Successful technologies do not necessarily lead to a positive impact on well-being. Although the main goal of introducing effective technologies is to increase productivity, income, and user well-being,[5] not all effective technologies can achieve this goal (Nwajiuba, 1995). The study of the social and economic effects of the introduction of new technologies is thus a challenge for research (IITA, 1990).

After years of efforts to generate and disseminate improved maize varieties, it is important to assess the impact of these technologies on the incomes and expenditures of farm households. This justifies this study on the adoption of improved varieties of maize and its contribution to improving the income and expenditure of maize farmers in the South Atlantic Department of Benin. The basic hypothesis is to test whether the adoption of improved varieties of maize increases the income of maize farmers.

MATERIALS AND METHODS

To evaluate the impact of improved maize varieties on the income and expenditure of maize growers in the South Atlantic Department of Benin, the econometric approach based on the calculation of the Average Treatment Effect (ATE) in English "Average Treatment Effect" (ATE) was adopted.

Let Y1 be the income or expenditure level for a maize grower i in Group 1 (adopters) and Y0 the same variable for maize grower i in the control group (non-adopters). Let $Di = 1$ be the binary variable when a maize grower has adopted at least one of the improved varieties and $Di = 0$, otherwise. The causal effect of adoption for this maize grower i is the difference between *Y1* and *Y0*: *Δi = Y1 − Y0*. The fundamental problem of impact evaluation is that one can not observe the "non-factual" elements corresponding to each technological or political change studied (Holland, 1986, Diagne and Demont, 2007). Thus,

to determine the impact Δi, there is a problem of missing data (Wooldridge, 2002). In the economic literature on impact assessment, this missing data are called the "counterfactual" (the non-factual elements) (Rubin 1977), which is the situation of adopting corn farmers if they had not adopted. Moffitt (1991) demonstrates that an average causal effect of a technological or political change in a population could be determined. The ATE will then be obtained.

$$ATE = \{\Delta i\} = \{Y1-Y0\} = \{Y1\} - \{Y0\}$$

The ATE measures the effect or impact of treatment on a randomly selected person in the population, which is the same as the ATE on all members of the population (Woodbridge, 2002; Beckmann, 1997).

In most cases, the impact is defined by the ATE on treated individuals (ATT or ATET) (Rosenbaum and Rubin 1983):

$$ATET = \{\Delta i/Di=1\} = \{Y1-Y0/Di=1\} =$$
$$\{Y1/Di=1\} - \{Y0/Di=1\}$$

To consistently estimate ATE, one must first know the probability of adoption. For this purpose, the matching or matching approach (Heckman *et al.*, 1998), better known in the French literature as the "paired groups" approach, was used.

The computational approach states that, as a first step, the propensity score is estimated as the predicted (or conditional) probability of adopting improved varieties.

$$P(x) = Pr(w=1/x) = Ei(w/x)$$

Where w = {0; 1} is the indicator of adoption, and x the vector of observable characteristics that determine adoption.

After estimating propensity scores, the ATE subgroup (ATET) can then be estimated as:

$$ATET = \{Y1-Y0/Di=1\} = Ei\{\{Y1-Y0/Di=1, (x)\}\}$$
$$= \{\{Y1/Di=1,(x)\} - Ei\{Y0/Di=0, (x)\}/Di=0\}$$

Several techniques have been developed to match adopters with non-adopters with similar propensity scores. The most commonly used techniques are stratification matching, nearest-neighbor matching, kernel matching, and radius matching.[6] In the case of this study, we opted for the closest neighbor matching technique.

Principles of propensity score matching method

The matching method is a non-parametric causal inference method. Control and treatment groups are likely to have different responses due to differences in their observable characteristics. To control these false differences, a control group consisting of individuals whose observable characteristics are the most matched possible to the treatment group is selected as the matched control group in the treated group. In principle, the selection bias is totally controlled when comparing two individuals with the same characteristics, since there are many features to be included in the comparison and there are enough individuals treated and not treated and treated among similar individuals.

This method assumes that the only differences between the two treated and untreated populations are their individual characteristics and treatment. If we neutralize the differences according to the characteristics, then only the effect of the treatment remains.

For untreated maize (non-adopting) household, $Y0i$ is observed while $Y1i$ is unknown.

The result variable observed, for each maize farmer's household, can, therefore, be inferred from the potential variables and the treatment variable by the following relation:

$$Yi = TiY1i+(1-Ti)\,0i \qquad (1)$$

Only the couple (Yi, Ti) is observed for each household maize grower. The causal effect of adoption (treatment) is defined for each maize farmer:

$$\Delta i = Y1i-Y0i \qquad (2)$$

This difference represents the difference between what would be the situation of the maize grower if his maize was treated (adopting) and what he would be if they were not. Thanks to hypotheses on the attached law of ($Y0$, $Y1$, and T), we can identify some parameters of the distribution of the causal effect from the density of the observable variables (Y and T). Therefore, estimating the effect of adoption for each maize farmer will not be possible and one must focus on the average effects of this treatment. Two parameters are usually the subject of a specific examination:

The ATE in the population

$$\Delta ATE = (Y1-Y0) \qquad (3)$$

The ATE in the adopting population

$$\Delta ATET = (Y1-Y0|T=1) \qquad (4)$$

Assumption of conditional independence and common support

The (unconditional) independence between the latent variables of the result ($Y0$, $Y1$) and the

assignment to the treatment T is a very unlikely hypothesis. A less restrictive condition is to consider that there exists a set of observable variables X conditionally to which the independence property between the latent results and the assignment to the treatment is verified. It is the hypothesis of independence conditional on observable characteristics.

$$(Y0, Y1) \perp T|X \qquad (7)$$

The condition of conditional independence for the identification of $\Delta ATET$ is less strong, since it requires only the independence between the potential result in the absence of treatment and the treatment, namely:

$$Y0 \perp T|X \qquad (8)$$

With regard to the common support hypothesis, it ensures that for each household treated; there are maize-growing households in the control group with the same characteristics observed:

$$0 < (T = 1 \mid X) < 1 \qquad (9)$$

For the estimation of $\Delta ATET$, this hypothesis is reduced to: $(T = 1|X) < 1$.

Under the two conditional independence assumptions and the common support, the allocation to the treatment is random and the result of the control subjects can be used to estimate the counterfactual result of the maize growers treated in case of nontreatment. The principle of estimation is to use the information available on untreated maize growers to construct a counterfactual for each treated individual.

Estimation of propensity scores and common support

Let us consider the ATE on the treaties:

$$\Delta ATET = (Y1-Y0|T=1) = \mathbb{E}(Y-Y0|T=1)$$
$$\Delta ATET = (Y - \mathbb{E}(Y|X, T=0)|T=1)$$
$$\Delta ATET = \mathbb{E}x|T=1((Y1|T=1, X=x) - \mathbb{E}(Y0|T=0, X=x) \qquad (10)$$

The final estimator of $\Delta ATET$ is then obtained as the average of the differences in the situation of the treated individuals and the constructed counterfactual. The problem is, therefore, to estimate for each maize producer of characteristics, the quantity $(Y0|X = xi, T=0) = g(xi)$. To do this, it is sufficient to match each maize household with maize farmers who have the same characteristics Xi (matching variables) or to do the matching based on the propensity scores $(X) = P(T=1|X)$ maize growers of both groups (matching the propensity score) and then estimating $g(xi)$.

In the following, we focus on the propensity score matching approach, which presents the various intermediate steps.

Propensity score
When estimating the propensity score, there are two choices to make: The estimation model to use as well as the variables to be included in this model. In principle, any discrete model can be used. However, compared to linear probabilistic models, there is a preference for logit or probit models. These models should include all observed variables that influence selection in treatment as well as the outcome. Higher-order terms or interaction terms should be included in the model specification only if they allow the estimated propensity score to satisfy the equilibrium property; that is, to have in each cell of the propensity score the treated and control units of the same distribution of the observed variables. It is proposed to use the logit regression model to estimate propensity scores.

Logit model
The logit model is one of the dependent variable qualitative models. It's used for the modeling of discrete choices and is made interesting by two properties: Its range is reduced from 0 to 1 and the possibility of being linearized by the logarithmic transformation (Abdoulaye, 2001).

Let Y be a binary variable with $yi = 1$ if adoption and $yi = 0$ if no adoption. Let "Z" be the vector of the variables contributing to the explanation of y.

$Zb = \Sigma Xii$ = Weighted Effects Matrix of all explanatory variables

Xi = Explanatory variables that may influence the adoption decision i = Parameters to estimate

Z = The matrix of explanatory variables b = The matrix of marginal effects

y can take the value 1 with the probability and the value 0 with the probability.

Common support
Once the score is estimated for all sampled maize households, the propensity score common support is determined to ensure that for each adopting maize household, at least one non-adoptive maize farmer household can be found. Same propensity score. To build the common support of the propensity score, two approaches can be adopted. The choice of the appropriate approach depends on the distribution

of the propensity scores of the two groups. The first approach is based essentially on the comparison of the minimum and maximum propensity score in the two groups of maize-growing households. The basic criterion of this approach is to delete all observations with a lower (and larger) propensity score than the minimum (or maximum) control group (non-adopting). However, there are some problems related to the comparison of minima and maxima (for example, if there are observations within the limits that are discarded even if they are very close to the limits). Another problem arises if there are maize-producing households in the common support interval where there is only a limited overlap between the two groups (e.g., in an interval, only processed observations can be found). Additional problems arise if the tails of the distribution are very thin (example the important distance between the smallest maximum and the second smaller maximum).

The second approach, suggested by Smith and Todd (2005), is a way to get around these problems. This approach is based on estimating the density of the distribution in both groups ("trimming" procedure). It consists in defining the region of the common support by the values of P which have a positive density for the distributions $T = 0$ and $T = 1$.

Description of the variables of the model

The dependent variable is the adoption or not of improved varieties of maize. It is, therefore, binary and takes the value 1 if the household adopts improved varieties of maize and 0 otherwise.
The observable variables of the study are as follows:

- Maize Age: This variable measures the age of the maize grower in years.
- Maize farmer education: This variable is set to 1 if the maize farmer is educated and 0 otherwise. It is thought that the heads of households who have received an education will further educate their children. Indeed, studies show that parents' level of education has a positive influence on children's education in a sense that instructed and educated parents value the economic and social value of education and tend to opt for support for schooling. Their children (Zahonogo, 2001).
- Membership of a group: This variable takes the value 1 if the head of household is a member of a group and 0 otherwise. The fact of belonging to a socio-professional group improves the technical and therefore productive efficiency of the agricultural producer.
- Area planted: This is the area that the household spends on corn production. The larger this area, the greater the income and the more the household will seek to adopt. The expected sign for the coefficient of the area is positive.
- The sex of the farmer is a binary variable that takes the value one if the head of the household is a man and 0 if he is a woman. Because men have more access to extension services and agricultural inputs than women (Traoré and Dabo 2012), the sex of the head of the household will have a positive effect on the adoption of varieties.

Sampling

The Atlantic Department is the second largest maize production area in Southern Benin (according to the production statistics of the DSA). It has 8 municipalities of which 4 have been chosen to constitute the primary unit, i.e., a survey rate of 50%. The 8 communes of the department have in the past sheltered tests/tests of extension on the improved varieties of corn. The common samples are randomly selected from the official and complete list of administrative communes of the Atlantic with the number of agricultural households in 2013.

At the level of the communes selected, a broad list of maize farmers' households having adopted at least one of the improved maize varieties and another list of households that did not adopt an improved variety of maize was established. An adopting household is defined as any household in which all members producing maize have adopted at least one of the improved varieties. It is also considered to be a household that has not adopted one of the improved varieties of maize, any household from which no maize grower has adopted an improved variety. These lists by commune served as a sampling frame for the random draw of the households of the maize farmers surveyed.

The minimum size of the sample surveyed was determined from the following formula of Dagnelie, (1998) at the 95% threshold:

Or

- $n1$ is the minimum number of households of maize growers to investigate

- Is the factor to reach a 95% confidence interval
- p is the proportion of maize households adopting the improved maize variety obtained from the results of ADEGBOLA and al. (2010) p = 0.898; and
- *d*2 is the margin of error that we want. In our case d = 5%

So *n*2 = 140

To make a comparison of the situation of households adopting improved varieties and non-adopters in the same communes, two homogeneous groups were set up for the collection of data:

- 72 maize farmers who have adopted at least one of the improved varieties
- 72 maize farmers who did not adopt an improved variety.

Data collection

Field data were collected on the basis of a questionnaire designed for this purpose. The main components of the questionnaire are sociodemographic information of the household; the adoption status of improved varieties of maize; the average annual consumption expenditure of the household (health, education, food, and others); and average annual agricultural and non-agricultural income.

Data processing and analysis

Information from the field was analyzed, coded, entered, edited, and processed using the Excel 2013, SPSS 21, and STATA 13 software. Descriptive analyses were performed using the central trend, position, and form used in descriptive statistics to characterize the surveyed population. Multi-varied analyses accompanied by statistical tests were carried out. The different standard methods used to describe the assignment to treatment are the average comparison tests (student test or analysis of variance), distribution comparison tests (Chi-square) and a series of regressions multi-varied logistics. All this aims at identifying the variables that can potentially be integrated into the construction of the score.

Finally, the econometric analysis of estimation of causality indicators ATE and ATET was also calculated to assess the impact of the adoption of improved varieties of maize on income.

RESULTS

The results are as follows:

It is found that 56.9% of adopters were members of a group against 43.1%. There is a link between membership in a group and the adoption situation. With regard to the producers' access to land, it is found that most of the adopters buy or rent land for corn production while the method of acquisition of land by the adopters is for most donations, sharecropping, inheritance, or loan. Hence, they do not invest in the extension of their fields.

Table 1 summarizes the quantitative characteristics of maize growers in relation to their adoption status. The average size of maize households according to the adoption situation is almost identical. The difference is very small and not significant. The same is true of the average age of corn growers. On the other hand, the differences observed in the "Years of experience of the maize grower" and "area planted" variables according to the adoption situation are significant. Thus, the average number of years of maize cultivation and the number of areas planted have a positive and significant influence on the adoption of maize varieties.

Quantitative variables observable adoption status average *t*-test for equality of means

Mean difference t ddl Sig. (Bilateral)

Household Size No Adoption 6.85, 542 1.239 142, 217

Adoption 6.31

Age passed No Adoption 44.29 −2.681 −1.529 142 0.128

Adoption 46.97

Years of experience No Adoption 20.38 −3.444 −2.014 142 0.046

Adoption 23.82

Area planted No Adoption 1.86 −1.964 −4.562 142, 000

Adoption 3.82

Source: Survey data, 2017

Differentiated analysis of the impact indicators selected

The results obtained in Table 2 indicate that the average net income of the maize farmers who adopt the improved varieties is CFAF 1612951.97 per year, compared to CFAF 400214.42 for non-adopters. The difference is significant at the critical threshold of 1% between these two incomes. The

Table 1: Quantitative characteristics of maize farmers in relation to their adoption status

Quantitative variables observable	Adoption status	Average	*t*-test for equality of means			
			Difference of average	*t*	DDL	Sig. (bilateral)
Household size	No adoption	6.85	0.542	1.239	142	0.217
	Adoption	6.31				
Age passed	No adoption	44.29	−2.681	−1.529	142	0.128
	Adoption	46.97				
Years of experience	No adoption	20.38	−3.444	−2.014	142	0.046
	Adoption	23.82				
Area planted	No adoption	1.86	−1.964	−4.562	142	0.000
	Adoption	3.82				

Source: Survey data, 2017

Table 2: Differentiated analysis of the impact indicators selected

Outcome variables	Adoption status	Average	Average of the difference	Sig. (Bilateral)
Household Income	Not adopting	400214.42	1212738	0.000
	Adopting	1612951.97		
Annual food expenditure	Not adopting	491083.33	21617	0.823
	Adopting	512700.00		
Education expenditure	Not adopting	94697.68	133269	0.001
	Adopting	227966.90		
Health expenditure	Not adopting	56713.89	54065	0.030
	Adopting	110779.18		

Source: Survey data, 2017

adoption contributes to an increase in net income of 1212738FCFA between the two subpopulations studied.

The analysis of Table 3 shows that the expenditure invested in health by households adopting maize farmers is CFAF110779.18 per year, compared to CFAF56713.89 for non-adopters. The difference is significant at the critical threshold of 5% between these two expenses. Adoption thus contributes significantly to the improvement of the health expenditure of maize farmers.

With regard to education expenditures, the analysis of the table below shows that households adopting improved varieties spend in education 227966.90 FCFA per year, compared to 94697.68 FCFA for non-adopters. This suggests that school-aged children were more enrolled in school in adoptive households than in non-adopters. The difference of 133269 is significant at the critical threshold of 1%. The adoption of improved varieties of maize, therefore, leads to an increase in the expenditure allocated to education.

The analysis of Table 3 shows that the expenditure invested in food by households adopting maize growers is 51,270,000 FCFA per year, against 49,108,333 FCFA for non-adopters. However, the difference is not significant at the critical threshold between these two expenses. This can be explained

Table 3: Independence test results with the adoption of improved varieties

Variables	Test à b		
	Chi-square	Dof	Asymptotic meaning
Sex	8.014	1	0.0046
Education	1.505	1	0.2199
Membership to a group	2.758	1	0.0967
Ways of access to land	0.622	1	0.4304
Household size	1.742	1	0.1868
Elderly age of the head of household	1.849	1	0.1739
Years of experience of the head of household	4.993	1	0.0255
Area planted	35.403	1	0.0000

by the existence of self-consumption at the level of maize-growing households. Therefore, adoption does not significantly contribute to improving the food expenditure of maize farmers.

Outcome variables Adoption status Mean Average difference Sig. (Bilateral)

Household Income Not Adopting 400214, 42 1212738 0.000

Adopting 1612951.97

Annual food expenditure Not adopting 491083.33 21617 0.823

Adopting 512700.00

Expenditures on Education Not Adopting 94697.68 133269 0.001
Adopting 227966.90
Health Expenditure Not Adopting 56713.89 54065 0.030
Adopting 110779.18
Source: Survey data, 2017

Propensity score modeling

The logistic regression model for propensity score modeling. For the choice of variables to be introduced in this model, a test of independence between the treatment variable "adoption situation" and the observable characteristics that were retained. The test results are shown in Table 3.
B-test
Chi-square Dof Asymptotic Meaning
Sex 8.014 1, 0.0046
Education 1.505 1, 0.2199
Membership to a group 2.758 1, 0.0967
Ways of access to land, 0.622 1, 0.4304
Household Size 1.742 1, 0.1868
Elderly Age of the Head of Household 1.849 1, 0.1739
Years of experience of the Head of Household 4.993 1, 0.0255
Area planted 35,403 1, 0000
at. Kruskal Wallis test
b. Group criterion: Adoption status
At the 5% threshold, the distributions of the variables "sex," "years of experience of the head of household," and "area planted" are not identical on the categories of the situation of adoption. The differences being significant, these variables are dependent on the adoption or not of the improved varieties. The same applies to the variable "membership in a group" at the 10% threshold. On the other hand, the variables "education," "Mode of access to land," "household size," and "age of head of household" are independent of the adoption or not of improved varieties. These are the four variables that we used in the modeling of propensity scores.
Before estimating propensity scores, we treated the atypical observations according to these four explanatory variables because it may have observations whose values for the explanatory variables would significantly influence the coefficients of the logit model (or even its statistical validity) which estimates the propensity

scores. The final estimate of propensity scores by logit regression does not take into account atypical observations.
To make sure that for each adopter, we can find at least one non-adopter in the database that has at least the same characteristics, we build the common support region of the propensity scores. To achieve this, we compare the maxima and minima of the distribution of propensity scores for both groups. We remove maize farmers from the (adopting) treaty group whose scores are either lower or higher related to, respectively, the minimum and maximum scores of the maize farmers in the control group. The common support region that we obtain is the interval (0.2798; 0.738). Graph 3 presents the distribution of the propensity scores in the common support region for the treatment group (adopting) and the control group.
Having determined the propensity scores, we divide the sample into equitable blocks of the propensity score. The optimal number of blocks is 1. Thus, 69 maize farmers who adopted at least one of the improved varieties were matched to 63 non-adopting maize farmers based on the observable variables independent of the variable status of adoption. The following Table 4 shows the characteristics of the optimal block.
Bloc Number Adoption Status
No Adopting Adopting Total
Optimum block 1 63 69 132
Source: Results obtained from survey data, 2017

Analysis of the impact of the adoption of improved varieties of maize on the income of maize farmers

*Impact of adopting improved varieties of maize on income*
The analysis of the results of Table 5 shows that the adoption of improved varieties of maize resulted in an average improvement of the net income of 1074986 FCFA (ATE) and 1169430 FCFA (ATT), respectively, in the population of maize-growing households (adoptive parents and nonadoptants),

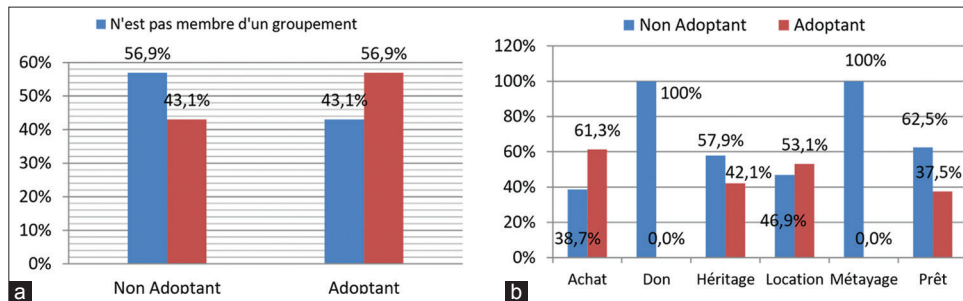**Table 4:** Optimal number of blocks and distribution of matched corn producers

Bloc number		Adoption status		
		No adopting	Adopting	Total
Optimum block	1	63	69	132

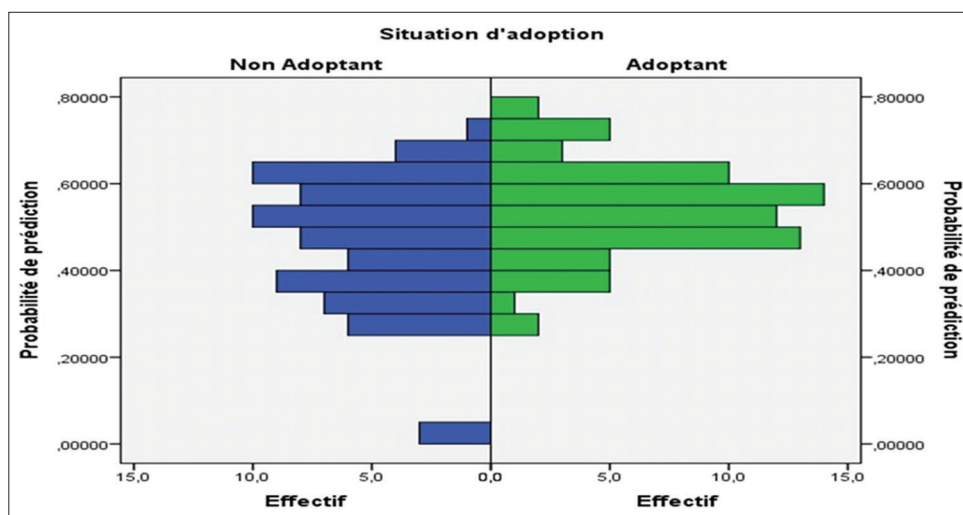Source: Results obtained from survey data, 2017
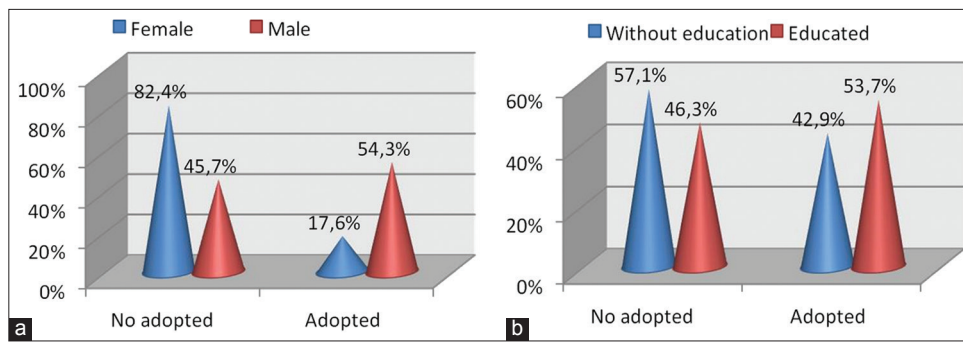
Graph 1: (a and b) Characterization of maize farmers by adoption status and level of education. Source: Survey data, 2017

Graph 2: (a and b) Characterization of maize farmers according to their adoption situation, land ownership, and group membership. Source: Survey data, 2017

Graph 3: Distribution of propensity scores in the common support region

Table 5: Average effect of adoption on income

Revenu des Ménages	AI Robust				
	Coef.	Standard error	z	P>|z|	95% Confidence interval
ATE	1074986	232407.6	4.63	0.000	619475.8–1530497
ATET	1169430	166991.8	7.00	0.000	842131.8–1496728

Source: Results obtained from survey data, 2017

and within households adopting maize farmers. The relative difference between ATET and ATE is 8.78%. This difference is positive and statistically significant at the 1% level.

The adoption of improved varieties of maize, therefore, has a positive impact on the net income of maize farmers as it increases the income by 8.78% compared with the ATE. It can be seen that

adoption contributes significantly to improving the income of maize farmers.

DISCUSSION

Improved maize varieties: The IITA, in partnership with agricultural research centers, has developed improved maize varieties through

conventional plant breeding using the available characteristics. These varieties have the potential to give farmers the opportunity to meet the challenges of maize production in West and Central Africa. They aim to overcome the major obstacles to maize production in the subregion, such as drought, low soil fertility, pests, diseases and parasitic plants, and so on. This improved corn comprises 13 open-pollinated varieties that are resistant to *Striga hermonthica*, stem borers, and drought. They have a good adaptation to a low nitrogen soil, according to these same researchers.

In addition, the use of these hybrid and stress-resistant varieties will promote the adoption rate of improved maize cultivars by farmers, which will contribute to increased maize production and increased food security.

Impact evaluation

Program evaluation can be defined as the systematic collection of information about the activities, characteristics, and products of a program to make judgments about it, to improve its effectiveness and/or assist in the decision for future programming (Patton, 1997, Cited by Horton and Mackay, 2003).

This definition is appropriate for all three types of evaluation: The ex-ante evaluation, which aims to collect and process the information needed to estimate the effects of a future program; in-service evaluation, which feeds on the implementation monitoring data of the activities, with a view to their eventual reorientation; and the ex-post evaluation, which takes place more or less long after the end of the program, and provides information on the actual progress of the program and its impacts.

The term "impact" is rarely defined in isolation, but literature indicates that it is most often the variation of an indicator chosen to reflect the achievement of program objectives. The impact may, however, refer to potentially unwanted or indirect consequences of the intervention such as, for example, environmental effects. For this work, "The impact evaluation intended to measure (...) whether the program has had the desired impact on individuals, households, and institutions and whether these effects are attributable to the intervention of the program." Impact evaluations can also explore unintended

consequences, either positive or negative for beneficiaries.[7] A key aspect, underlined by this definition, is that it must be possible to determine whether the effects observed can actually be attributed to the program. This issue of attribution or, otherwise, the causal link between the program and the measured impacts is at the heart of the evaluation methods. In addition, the term "measure", used in this definition, refers to the interest of quantifying the impact.

Adoption of technology

The adoption of an innovation is a decision that allows the full use of a new idea as the only way to solve a problem (Rogers, 1983). According to Van den ban *et al.* (1994), adoption is a mental process that begins from the individual's first contract with innovation to the stage of rejection or acceptance. From this definition, researchers conceptualized adoption as a process that occurs over time and consists of a series of actions. Rogers (1983) and Adams (1982) distinguished five phases in this series:

- The knowledge which is the information phase;
- The interest phase where the individual develops an active desire to have more information on innovation;
- The evaluation phase where the individual compares innovation to existing practices and their requirements to their current situation.
- The experimentation phase where the individual tries the small-scale innovation to see in a practical way its performances.
- The adoption phase where the individual uses innovation continuously and on a large scale with satisfaction.

It depends on the socioeconomic characteristics of prospective adopters, the information they receive and how they use them (Feder and Umali, 1993, Rogers, 2003) as well as conditions for accessing necessary resources. It also depends on the structure and nature of the exchanges they have with their social networks and their interactions with the institutions that accompany the transfer of innovations, especially agricultural extension (Ali-Olubandwa *et al.*, 2010; 2008, Rogers, 2003, Young, 2007).[8] It also depends on the compatibility of the characteristics of the

innovations with the institutional environment (norms, rules, and values), technological (existing technical systems, know-how, and risks), and economic (accessibility of the necessary factors of production) of potential adopters and the perception that they have on the characteristics of the innovations that has been proposed to them and the consequences of these on their standard of living (Rogers, 2003). Farm income: The income of a household is the sum of monetary and non-monetary incomes. It consists of cash and in-kind receipts that are collected by household members at more or less regular intervals.[9] For the International Labor Organization, household incomes can be viewed from the point of view of their use for policy analysis as the best proxy for the economic well-being of individuals and households. According to the same organization, three principles are generally debated when defining income for a given reference period:

- Revenues should be kept as regular and recurring to be considered income
- To be considered as income, revenues should contribute to current economic well-being.

Many authors have proposed approaches to defining the concept of income taking into account one or other of the principles raised. A widely quoted income concept, developed from economic theory, is Hicks'.

Hicks (1946) defines income as the maximum amount of money an individual can spend this week knowing that he or she can spend the same amount in real terms each of the following weeks. The three principles mentioned above are all explicitly or implicitly integrated into this approach.

Farm income is the difference between production and expenses related to this production. There are two types of income: Gross income and net income. The first type is the difference between gross output and actual expenses paid for this production. The costs include the costs of variable inputs, i.e., seeds, different fertilizers, insecticides, and labor costs (clearing, plowing, sowing, weeding, and harvesting). It is calculated for a single crop year.

CONCLUSION

The adoption of improved maize varieties in the Atlantic Department of Southern Benin has led to an improvement in the annual net income of 1169430FCFA (a relative effect of 1.066%), health expenditure (a relative effect of 15.88%), and expenditure on education (a relative effect of (16.08%). The adoption of improved maize varieties has a positive impact on household net income. The analysis of the determinants of adoption showed that the factors that influence the adoption of improved varieties of maize are sex, the year of the head of household, the area planted, and the membership to a group.

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