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Research Article

ANALYSIS OF THE EFFECTS OF THE ADOPTION OF NEW TECHNOLOGIES ON THE WELL-BEING OF TOGOLESE AGRICULTURAL HOUSEHOLDS

[1, *]Vicente M. Martínez Cárdenas and [2]Vivian R. Mena Miranda

[1] Children's Medical Center, Lake City, Florida, Estados Unidos
[2]Hospital Pediátrico Universitario Centro Habana, La Habana, Cuba

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Abstract

This article aims to analyze the effects of adopting new agricultural technologies on the well-being of Togolese households. The propensity score and the instrumental variable methods were used to correct selection and endogeneity biases based on data from the Harmonized Household Living Conditions Survey (EHCVM 2018). The results reveal that gender, area, use of plant protection products, crop association, and region of ownership are the main determinants of improved seed adoption. Furthermore, adopting improved seeds has a significant and positive effect on household consumption expenditure and reduces the number of households with income below the poverty line. Indeed, households using improved seeds saw their total consumption and food expenditure increase by 7 points and 0.105 points, respectively, compared to households not using them. These results suggest an intensification of sensitization of farm households to adopt new agricultural technologies, especially improved seeds, to reduce the poverty rate in rural areas.

Keywords: Improved seeds, Poverty, Consumption expenditure, Farm household.

INTRODUCTION

In recent years, many developing countries have implemented macroeconomic, sectoral, and institutional reforms to achieve high and sustainable economic growth, food security, and poverty reduction (Asfaw, Solomon *et al.,* 2012). Despite these various reforms, growth in the agricultural sector still needs to be improved to adequately address poverty, achieve food security and lead to sustained GDP growth on the African continent (Dessy *et al.,* 2006). More worryingly, the sector remains characterized by low utilization of modern technologies and low productivity, which prevents it from meeting the growing food needs of a growing population. However, the agricultural sector is a key component of programs to reduce poverty in these countries (Ogundari, 2014) by promoting agricultural innovation and technology (Kebebe, 2017). De Janvry & Sadoulet (2002) As noted by De Janvry & Sadoulet (2002), adopting agricultural innovations and technologies is essential to ensure food security and poverty reduction, potentially increasing farm household income and reducing the market price of staple foods. Adopting new agricultural technologies can reduce the cost of production per unit, increase food supply, raise producers' incomes, and lower consumer food prices. It can also create large-scale multiplier effects within the rural community, leading to job creation in industries related to agricultural production, such as value-added processing and roadside marketing (Moyo *et al.,* 2007). Various theoretical frameworks have been developed to study farmers' decisions to use new technologies (Feder & Slade, 1984; Abadi & Pannell, 1999; Negatu & Parikh, 1999; Isham, 2002). According to a human capital model of technology diffusion proposed by Feder & Slade (1984), farmers with more extensive land tracts and higher education levels have better knowledge of improved agricultural technology.

Corresponding Author:** ***Vicente M. Martínez Cárdenas
Children's Medical Center, Lake City, Florida, Estados Unidos

They are, therefore, more likely to incorporate technology more quickly into their farms. This argument was extended by Isham (2002), who included social capital as a fixed input in adopting improved technology. His model posits that farmers with larger workforces, and those whose neighbors use improved technologies, accumulate more information and adopt new technologies more quickly. According to Negatu & Parikh (1999), technology is transferred from sources such as extension agents and the media to the farmer depending on the farmer's characteristics, factor endowments, and prevailing agroecological, socioeconomic, and institutional factors. Indeed, technologies are often designed to benefit farmers by improving soil fertility, conserving soil nutrients, water, and other natural resources, increasing yields, improving pest control, mitigating the effects of climate change, and assisting in farm mechanization (Ogundari & Bolarinwa, 2018). Work in the literature shows that adopting agricultural technologies can, directly and indirectly, reduce poverty (Becerril & Abdulahi, 2010; Moyo *et al.,* 2007). Direct effects include productivity gains and low cost of production that can improve adopters' incomes. At the same time, indirect benefits of technology adoption can take the form of increased supply that can lower food prices. Increased productivity can also stimulate labor demand, leading to increased employment and income for the poor, who usually provide farm labor. Adopting improved technologies has been identified as a key measure to achieve food security (Langyintuo *et al.,* 2008). Farmers have the opportunity to improve their welfare as well as their food security if they use improved agricultural technologies (Mendola, 2007). In Togo, the increase in agricultural production is linked to increased cultivated land. This fact can only be understood by analyzing Togolese agriculture's overall socioeconomic context. The country has a surplus of food production, but most rural people suffer from food insecurity. According to the World Food Programme (WFP, 2018), more than 800,000 people do not have access to food that would enable them to absorb the 2,100 kilocalories per day recommended by the Food and Agriculture Organization of the United Nations (FAO)[1] . This places Togo 81st out of 117 countries, with a score of 23.911 considered "severe" in the 2019 World Hunger Index. The country has low production and productivity rates, accentuated by strong variations from one year to the next, and insufficient incomes felt most in rural areas. This is at the root of chronic malnutrition and food insecurity among farming and low-income households. In addition to these constraints, climatic shocks, particularly floods, droughts, irregular rainfall, late rains, and high winds, negatively impact productivity and food production. The effects are particularly evident among smallholders, for whom productivity growth in all cereals (maize, sorghum, millet, and rice) has been almost zero in some years, and productivity per hectare of primary food crops has been lower than that of neighboring countries. These smallholders use few inputs and have no access to extension services in 95% of cases. (APRM, 2014). In addition, inadequate control of water resources, poor infrastructure and storage systems, and lack of storage facilities undermine the sustainability of food systems. In addition, although women make up more than half of the active agricultural population, they have limited access to credit, inputs, and agricultural equipment. As a result, annual growth in agricultural production was 30 percent for cereals, 24 percent for tubers, and 167 percent for vegetables (VerTogo, 2018).

A literature review shows that more and more work is being done on adopting agricultural technologies and their impact on households. However, this work is based more on the determinants of the adoption of agricultural technologies without focusing on particular aspects of technologies adopted, mainly in the case of Togo. Thus, this research aims to analyze the impact of adopting new agricultural technologies on household welfare in Togo. This research hopes to shed new light on the impact of adopting new agricultural techniques on household welfare. As Asfaw et al. (2012) show, it isn't easy to assess the influence of technology adoption on farmer welfare due to unobserved variability and likely endogeneity. First, there could be a bi-causality between technology adoption and farmers' welfare. Technology adoption may lead to increased agricultural productivity and improved welfare. However, improved farmer welfare may lead to increased technology adoption. In terms of observed heterogeneity, farmers who adopt the technology may differ from those who do not adopt it regarding income level or welfare. We address this issue by using propensity score matching, quantile regression, and instrumental variable methods. The remainder of this paper presents the elements of empirical analysis of the effect of adopting new technologies on agricultural productivity in the next section. Section 3 highlights the analysis methodology. The results and their interpretations are presented in the fourth section, and the last section presents the conclusion and policy implications.

An empirical review of the effects of adopting new agricultural technologies on poverty

The effects of adopting new agricultural technologies on poverty and development have been the subject of several empirical studies. In the development context of African countries, agriculture remains the most important sector in most economies in terms of employment (those working in agriculture account for about 57.9% of the population), food supply, and income for 10-25% of urban households (World Bank, 2016). Referring to United Nations data, it is worth noting that most people in sub-Saharan Africa live in rural areas (61.4%). Most Africans work in agriculture (57.3%). Existing empirical work shows that agricultural growth is a good policy for poverty reduction because agro-cultural growth generated by R&D expenditures is relatively cheap. Indeed, in Africa, Asia, and Latin America, Thirtle, Lin, & Piesse (2003 op. cit.) find that investment in agricultural R&D sufficiently increases the agricultural value added. For these authors, agricultural productivity growth leads to sufficiently high growth to pay for the R&D investments needed to generate the required technologies, substantially affecting poverty reduction. Overall, they showed that a 1% increase in yields reduces the number of people living on less than a dollar daily by six and a quarter million, 95% of them in Africa and Asia. Overall, their results show that, among people living on less than a dollar a day in Africa and Asia, agricultural yields increased by 4.5% per year. Ceteris paribus resulted in an annual reduction in dollar-a-day poverty on both continents of 26.7 million, or 2.45% of the total number of people in this poverty bracket (Thirtle *et al.,* 2003). To further elucidate their results, it is worth noting that yield increases had 73% and 67% of the impact of per capita income increases for Africa and Asia, respectively.

Dontsop Nguezet et al. (2020) also showed that cropping system intensification (CSI) technology enhanced crop yields, crop revenue, and per capita consumer spending in Africa's Great Lakes area (which encompasses Burundi, eastern DR Congo, and Rwanda), resulting in poverty alleviation. Using the production and consumption behavior of a farm household, they assessed the impact of the adoption of CSI technologies on variables of interest such as consumption expenditure. Indeed, using the endogenous switching regression (ESR) model, their results showed that the gain in farm income and, thus, consumption expenditure due to the adoption of CSI technologies reduced poverty by 13% points in eastern DR Congo, 6% points in Rwanda, and 2% in Burundi. As a result, the number of poor people who have managed to overcome poverty is estimated at 99,653 in eastern DR Congo, 75,972 in Rwanda, and 4,358 in Burundi.

Similar results are found by Fan et al. (2000) in India. Using selected Indian data, they estimated the returns to alternative investments in rural areas in terms of agricultural productivity and poverty reduction. Their results show that the most significant impacts on these two variables come mainly from investment programs directed toward roads, R&D, and agricultural extension. In Malawi, Bezu et al. (2014) used the instrumental variable model to control for the possibility of endogeneity and selection bias due to factors affecting the adoption decision of improved maize varieties. Their results show that adopting improved maize varieties positively affects producer home consumption, income, and assets. Using the propensity score matching method, Becerril's (2010) study found that adopting improved maize varieties contributes to an increase in per capita household expenditure of about 136 to 173 pesos in Mexico. Also, adoption reduces the probability of being poor by 19-31%. These results corroborate those of (Alwang & Siegel, 2003) and Alwang and Siegel (2003). Using a Probit model, they could show that agricultural research enabled the adoption of new maize varieties, which

[1] WFP. 2018. Zero Hunger Strategic Review in Togo. https://www.wfp.org/publications/togo-strategic-review

positively impacted poverty reduction and income inequality, reducing the Gini coefficient for rural areas from 55.0 to 54.2. In Nigeria, Wossen *et al.,* (2017), using an endogenous switching regression (ESR) approach, observed productivity gains and risk reduction following adopting drought-tolerant maize varieties. Their results show a 12.9% reduction in the incidence of poverty (corresponding to 2.1 million people lifted out of poverty) and an 83.8% reduction in the probability of food shortage among adopters. Kijima *et al.,* (2008) also found that the introduction of the New Rice for Africa (NERICA) increased per capita income by USD 20 (12% of real per capita income) and a reduction in the incidence of poverty by five percentage points. Using an endogenous switching regression, the analysis of (Asfaw *et al.,* 2012) Asfaw et al, (2012) reveals that the adoption of improved agricultural technologies has a significant positive impact on consumption expenditure (in adult equivalent terms) in rural Ethiopia and Tanzania. This confirms the potential role of technology adoption in improving the welfare of rural households, as higher consumption expenditure associated with improved technologies translates into reduced poverty, greater food security, and improved risk resilience.

METHODOLOGY

This section presents the theoretical framework for analyzing the impact of adopting new agricultural technologies on household welfare, the estimated models' empirical specification, the data presentation, and the variables' definition.

Theoretical model of the effect of the adoption of new agricultural technologies on poverty

Following Singh, Squire, and Strauss (1986), we used the standard economic model that combines a farm household's production and consumption behavior to assess the impact of technology adoption on variables of interest such as consumption expenditure. A farm household is assumed to maximize consumption utility under a combined budget, production, and time constraints. The optimal household choice problem is defined as follows:

$$max_{x \in S(z)}\, U(x,z) \tag{1}$$

where U (-) is the household utility function; x is the set of choice variables, including consumption and production; z is the nonchoice variables that can affect the utility function U; and S(z) is a set of constraints.

The maximization of household utility under the combined (budget, production, and time) constraint shows that the household can choose the level of consumption and the inputs used in agricultural production.

$$max_{c,x1,..xj}\{\dot{U}(c,z_u): s.t.\, p_c.c = p_r * \left(\sum_{j=1}^{j} f(x_j,z_j)\right) - \sum_{k=1}^{k} p_k \sum_{j=1}^{j} x_{jk}\} \tag{2}$$

where c denotes the vector of consumer goods with the corresponding price vector p_c; $x_j = (x_{jk})_{k=1,\dots k}$ the vector of inputs with the corresponding price vector, Pk ;z_u is a vector of household characteristics affecting household utility;z_j is a vector of different environmental characteristics affecting output; f is a production function and p_{ri} is the price of good i.

The optimal choices can be solved recursively in two stages. The first stage involves solving for the optimal choices of the inputs of production and generating the maximized value of profits, which will then be substituted into the combined constraint set ("full" income). The second stage involves solving for the optimal consumption choices by maximizing the household utility function subject to the "full income" constraint that contains the maximized value of profits.

The above theoretical exposition clearly shows that the solution to the household utility maximization first resulted in the optimal choice of production inputs that maximized profit. This captures the production behavior of the household. In the second stage, the household maximizes utility subject to the income constraint containing the maximized profit value. The solution to this utility optimization resulted in the optimal choice of consumption goods, capturing the consumption behavior of the household. The combination of the production and consumption behavior would capture the economic behaviors of the household, leading to poverty analysis.

A rational household is assumed to adopt a technology if the utility of adoption is greater than that of non-adoption. However, since we cannot observe the utilities, we define adoption criteria as follows:

$$C_i^* = \alpha Z_i + \epsilon_i avec\, C_i = \begin{cases} 1 \text{ if } C_i^* > 0 \\ 0 \text{ if not} \end{cases} \tag{3}$$

where C* is the difference between the utility of adoption and non-adoption for household i ; C_i represents the observed adoption status, where C_i = 1 for adopters, and C_i = 0, otherwise; α denotes a vector of parameters to be estimated;z represents household and farm level characteristics; and $\epsilon_i$is the random error term.

Empirical models to estimate the effects of new technology adoption on poverty

The empirical model specified below to assess the effect of adopting new technologies including improved seeds, on household poverty is based on Geffersa et al. Adopting improved seeds can provide additional resources to households to purchase food and is expected to improve nutritional well-being. However, the adoption of these technologies is voluntary and an individual decision. Therefore, an instrumental variable approach with binary participation in adopting improved technologies and a welfare outcome is suitable for estimation.

Following the theoretical household welfare function (equation 3.5), the empirical model is specified as follows:

$$\mathrm{W_{it}} = \Psi_0 + \Phi \mathrm{A_{it}} + \Psi \mathrm{Z'_{it}} + \mathrm{e_{it}} \tag{6}$$

where $W_{it}$is a welfare outcome variable for household i at time t ; A_{it} is an indicator of adoption of new technologies; Z'_{it} is a vector of control variables, Φ and $\psi$are the vectors of parameters to be estimated; and Ψ_0 and e_{it} are the intercept and disruption terms, respectively.

In this household welfare specification (equation 3.6), unobservable household heterogeneity is controlled using a household fixed-effects estimator, depending on whether the welfare measure is linear. The household fixed effects estimator is used when welfare is measured by household income and food consumption expenditure. Three indicators of well-being are selected for estimation: household income, household consumption, and food expenditure. However, it should be recalled that previous studies have explored several other measures of well-being, such as child nutrition (Manda *et al.,* 2019; Zeng *et al.,* 2017), food security (Shiferaw *et al.,* 2014), household consumption expenditure (Asfaw *et al.,* 2012; Bezu *et al.,* 2014) and household wealth (Manda *et al.,* 2019) In order to correct selection bias and endogeneity bias in this model while considering the heterogeneity of households according to their income or welfare levels, three estimation methods were used.

- **The instrumental variables method**

According to Barrett et al, (2012) it is essential to combine parametric and non-parametric models to enhance the robustness of the results as they are based on different assumptions. In this work, instrumental variable (IV) models, which effectively correct for endogeneity when the exclusion restriction condition is met, will be used. In this case, the risk of measurement error is low because producers have no interest in misreporting their participation in the new technology adoption project. The question is to see the effect of adoption on income, poverty, and food expenditure. The income, food expenditure, and poverty results are continuous variables, hence using linear models. Endogeneity is corrected using a two-stage least squares model (Angrist and Pischke, 2009).

In the ordinary least squares model, i is the individual, α is the constant, $\beta$is the coefficient associated with the individual and contextual characteristics of the producers (5), γ is the coefficient associated with the dummy participation variable (5), and ε is the error term.

$$Y_i = \alpha_1 + \beta_1 X_i + Y_1 D_i + \epsilon_i \quad (3.7)$$

To generate an unbiased estimate of the treatment, using instruments is an advantage as it isolates the part of the treatment variable that is independent of the unobserved characteristics that affect the outcome. The first-stage model consists of a linear regression of the treatment variable on the instruments **Z**and the vector of covariates. Linearity ensures that the residuals from the first stage are not correlated with the fitted values or the covariates (Angrist and Pischke, 2009). One of the difficulties in using IV models is the identification of instruments that meet the exclusion restriction condition (Wooldridge, 2010).

$$D_i = \alpha_2 + \beta_2 X_i + Y_2 Z_i + \mu_i \quad (3.8)$$

Instruments (Z) can be related to risk perception, such as risk aversion to participating in a program (Bellemare, 2012). They can also be linked to the village leader (Miyata, Minot, & Hu, 2009) or to the production area and extension offices (Girma & Gardebroek, 2015). In the EHCVM 2018-2019, the questionnaire that collected the information has several potential instruments. These are a geographical distance from home to extension services, perception of yield uncertainty, transport time from farms, soil fertility, distances (kilometers) between farms, soil type, etc... The two instruments used in the models are the ones that best meet the exclusion restriction. The first instrument is the soil type. The soil type determines the technology to be adopted. The second instrument is soil fertility level. The predicted values from this model are used in the second stage estimation (3.9) to retain the variations in the producers' results that are generated by the instrument. In (3.9), the ATT estimates the coefficient γassociated with the predicted values of new technology adoption.

$$Y_i = \alpha_3 + \beta_3 X_i + Y_3 \dot{D}_i + \epsilon_i \quad (9)$$

- **The SHP method**

The PSM model used is based on the work of Nakano et al, (2018). Assuming that it is an outcome of interest for plot j with the adoption of the new technologies, W_{oj} is the outcome of a household with the adoption of improved seeds on its plot, and the variable D_j a binary treatment indicator, where $D_j = 1$ if plot j is a plot using the new technologies and $D_j = 0$ if it is not, the average treatment effect on the treated (ATT) can be defined as follows:

$$ATT = E(y_{ij} - y_{oj}/D_j = 1) = E(w_{ij}/D_j = 1) - E(y_{oj}/D_j = 1) \quad (7)$$

where E(-) denotes an expectation operator. Under the assumptions of conditional independence and overlap, the following equation can be estimated consistently:

$$ATT^{PSM} = E[y_{ij}/D_j = 1, p(X_{ij})] - E[y_{oj}/D_j = 0, p(X_{ij})] \quad (8)$$

where $p(X_{ij})$ represents the probability of being a plot on which new technologies are adopted given observable characteristics $\mathbf{X_{ij}}$ household and plot level (Wooldridge, 2010).

Considering the sample's potential selection bias, farmers can be grouped in two ways.

Regime 1: Adopter $G_{1i} = \alpha_1 X_i \Theta_{1i} Z_{1i} v_{1i}$ (9a)

Regime 2: non-adopter $G_{2i} = \alpha_2 X_i \Theta_{2i} Z_{2i} v_{2i}$ (9b)

In these equations: G_{1i} and G_{2i} represent the farmer-level effect in regimes 1 and 2; X_i is the vector of exogenous variables assumed to determine the farmer-level effect. Θ_1 and Θ_2 are the parameters to be estimated; v_{1i} and v_{2i} are the error terms; Z_{1i} and Z_{2i} are instrument vectors that, by definition, have no effect on performance except through the adoption of improved seed varieties. The error terms are assumed to have a normal distribution, with a mean of zero and a covariance matrix (U) as follows.

$$\boldsymbol{\Omega} = \begin{bmatrix} \sigma_\mu^2 & \sigma_{1\mu} & \sigma_{2\mu} \\ \sigma_{\mu 1} & \sigma_1^2 & .. \\ \sigma_{\mu 2} & .. & \sigma_2^2 \end{bmatrix}$$

Where $\sigma_\mu^2 =$ var (μi), $\sigma_1^2 =$ var (v_2), $\sigma_{1\mu} =$ cov (μi,v_1), $\sigma_{2\mu} = cov$ (μi,v_2), Cov $(v_1\, v_2)$ is not defined because $G_1\, etG_2$ cannot be observed simultaneously. Moreover, the correlation between the error term of the selection equation and the outcome equation is not zero. Therefore, if $\sigma_{1\mu}$ and $\sigma_{2\mu}$are significant, the absence of selection bias is rejected.

Several authors, including Aryal & al, (2020); Freemana & al, (1998), Lee & Brown, (1985), Feder et al (1985) have previously used a two-step method to estimate the SHP model. They first estimated a probit model of the choice criterion equation, and the predicted variables γ_1 and$\gamma_2$representing the inverse of the Mills ratio were determined. These predicted variables are then used to estimate the system of equations. This system of equations can be written as follows:

$$G_{1i} = \alpha_1 X_i \beta_{1\epsilon} \gamma_1 \Phi_1 P_{1i} \eta_1 \quad (10a)$$

$$G_{1i} = \alpha_1 X_i \beta_{2\epsilon} \gamma_2 \Phi_2 P_{2i} + \eta_2 \quad (10b)$$

The coefficients of the two variables γ_1 and γ_2 provide the estimates of the terms $\beta_{1\epsilon}$ and $\beta_{2\epsilon}$. After the estimation of the variables, γ_1 and$\gamma_2$the residual values η_1 and η_2 cannot be used to calculate the standard deviations in the second stage estimates. However, according to Lokshin & Sajaia, (2004), the efficient method for estimating the SHP model in a single step is the maximum likelihood method. From another point of view, the average effect of access to improved seeds can be calculated as follows:

$$\text{ATT} = \text{E}(G_{1i} - G_{1i}/P_i = 1) = H_i(\alpha_1 - \alpha_2) + (\sigma_{1u} - \sigma_{2u})\gamma_1 \quad (11)$$

In this equation, $\text{E}(G_{1i}/P_i = 1) = X_i\alpha_1 + \sigma_{1u}\gamma_1$represents the expected outcome for farmers who have adopted the improved seed varieties, and $\text{E}(G_{2i}/P_i = 1) = X_i\alpha_2 + \sigma_{2u}\gamma_1$ is the expected effect for farmers who have not adopted these varieties.

- **The quantile method**

Regarding the farmer heterogeneity, it is necessary to perform a quantile regression to analyze the effect of new technology adoption on income. The quantile analysis is based on the following conditional independence assumption:

$$(Y_0, Y_1) \perp\!\!\!\perp \text{T}/\text{X} \quad (12)$$

This assumption corresponds to the conditional exogeneity of T (also referred to as selection on observables, i.e., all selections in the program can be explained by the observed variables X). To estimate the effect of new technology adoption controlling for the effect of observables X, matching methods are used to estimate the average treatment effect E(Y1-Y0) under the assumption (9) (Firpo, 2007) :

$$p(X) = P(T - 1/X) \in]0,1] \quad (13)$$

Equation (10) means that for every adopter, there is a non-adopter with the same observable characteristics (and vice versa). Firpo shows that under the above assumptions, it is possible to identify the two quantiles $q_T(Y_1)$ and $q_T(Y_0)$from the observed data alone (Y, T, X) through the relationships.

$$T = E\left[\frac{TI\{Y \le q_T(Y_1)}{p(X)}\right] = T = E\left[\frac{(1-T)I\{Y \le q_T(Y_0)}{1-p(X)}\right] \quad (14)$$

Analysis data

The data used in this article come from the Harmonised Survey on Household Living Conditions (HHLC) 2018-2019, which is part of the WAEMU Regional Statistical Programme (RSP) 2015-2020. The harmonized survey on household living conditions (EHCVM) was carried out using a two-stage probability survey with stratification at the first stage. This approach offers the possibility of representative results at the study area level. Furthermore, it makes it possible to have all the precision indicators of a probability survey (sampling error, coefficient of variation, confidence interval, etc.). The sampling method used is the two-stage sampling method with stratification in the first stage. The first-stage sampling frame is made up of enumeration areas (EAs) or clusters composed of 6,722 EAs. A study area is a part of the survey universe for which significant results are sought, i.e. separate estimates with sufficient precision. The different strata are obtained by combining the 05 regions with the two residential areas (urban, and rural). For the study, the commune of Lomé and its urban ring (Golfe Urbain) is considered a two-stratum study domain and excluded from the domain formed by the maritime region. In total, 12 survey strata were distinguished. In the first stratum, 540 DZs were drawn with a probability proportional to the number of households. In the second stage, a fixed number of 12 households were selected from each of the DZs selected in the first stage. The sample size for the HHVS is 6,480 households. It should be noted that the EHCVM was conducted in two waves, with the first wave covering 3,240 households (270 DZs). This represents half of the overall sample to be surveyed. The second wave occurred about six months after the first and involved the second half of the sample.

Description of model variables

First, this section presents the results of the descriptive statistics and then the results of the econometric estimations through the three methods described in the previous section.

Analysis of descriptive statistics

From the analysis of Table 1, the average age of the head of the household among adopters is 28.82 years with a range of 7.83 years. About the household size, it is, on average, about three individuals in households that have adopted improved seeds against 5 individuals in households that have not adopted improved seeds.

Table 1. Descriptive statistics of the quantitative variables used in the model

Features	Average	Standard deviation	Minimum	Maximum
	Household adopting technology			
Age of the head of the household	28.82	7.83	15	65
Household size	3.32	3.00	1	18
	Non-technology adopting household			
Age of the head of the household	28.67	11.15	15	92
Household size	5.11	2.81	1	21

Source: Author based on EHCVM data, **2018-2019**.

Table 2 shows that 9.43% of the sample adopted improved seeds compared to 90.57%. Of the adopting households, 65.17% have no education compared to 60.05% of non-adopters. These proportions are 15.56% and 14.91% for households with secondary education and above. In addition, at the primary level, the proportions of adopters (19.26) remain lower than those of non-adopters of the new seeds. According to the gender of the head of the household, men tend to adopt improved seeds than women. Indeed, the rate varies from 75.99% among male adopters to 24.01% among female adopters. On the other hand, among non-adopters, the rate is 64.99% for men against 35.01% for women. An individual's marital status can affect whether or not they adopt new technology. In our study, married and divorced individuals were found to be more likely to adopt new seeds than single individuals. The proportions of each group are 86.54, 10.29 and 3.17%, respectively, among adopters. Those members of an agricultural association or body also adopted the new seeds more, 93.40% against 6.60%. Moreover, among those who adopted improved seeds, only 5.80% have access to electricity against 94.20%. Finally, about the region, 42.48% of the adopters are from the savannah region and 36.94% in the Kara region against 2.11% in the maritime region.

Table 2. Descriptive statistics of the categorical variables used in the model

Features	Households adopting technology (%)	Households not adopting technology (%)
Level of education		
No level	65.17	60.05
Primary	19.26	425.04
Secondary and above	15.56	14.91
Gender of the head of the household		
Male	75.99	64.99
Woman	24.01	35.01
Marital status		
single	3.17	4.72
Married	86.54	71.76
Divorced	10.29	22.24
Member of a body		
Yes	93.40	96.18
No	6.60	3.82
Benefit from a social safety net		
Yes	98.15	3.40
No	1.85	96.60
Agricultural branch		
Yes	82.84	92.61
No	17.16	7.39
Access to electricity		
Yes	5.80	12.03
No	94.20	87.97
Agricultural region		
Maritime	2.11	12.58
Trays	13.72	20.81
Central	4.75	11.04
Kara	36.94	31.91
Savannahs	42.48	23.67
Sample size	9.43	90.57

Source: Author based on EHCVM data, 2018-2019

Statistical tests

Matching test on food expenditure: Figure 1A above shows the kernel density curves of the estimated propensity scores for the entire treatment group (adopters of improved seed) and the control group (non-adopters of improved seed). Analysis of the results reveals that the distribution of the treatment group is shifted to the right, indicating that those farmers who adopted improved seeds have higher propensity scores than those in the control group. This means that the farmers in the treatment group (adopters) have a higher average probability of income, thus showing a difference between the two groups. Since the two groups differ on the basic covariates, they must be balanced. The results of the balancing procedure show that the kernel density plots of the improved seed adopters and non-adopters groups overlap almost perfectly (Figure 1B). These plots show that the two groups have been balanced based on propensity scores. Thus, the two groups have the same characteristics, and thus only the adoption or non-adoption of improved seed is the difference between the two groups.

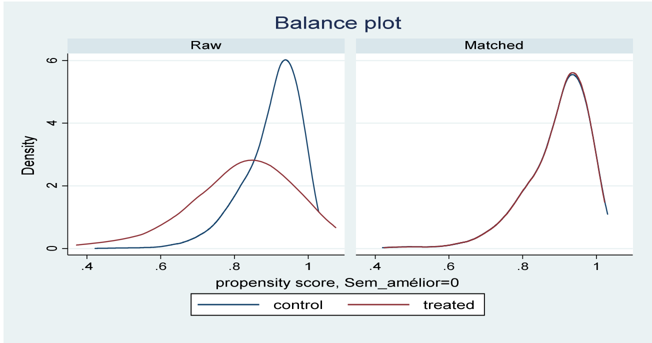

Figure 1A and 1B. Matching test on food expenditure

Test on average food expenditures

Another equally important test of the matching of the two groups (adopter and non-adopter) was carried out to check whether equilibrium was achieved on each of the basic covariates that enter into the calculation of propensity scores. Thus, Figure 2 presents the standardized mean difference distributions between the treatment and control groups for all covariates before and after matching against the estimated propensity scores. Again, analysis of the figures reveals a difference in means for most covariates close to 0.

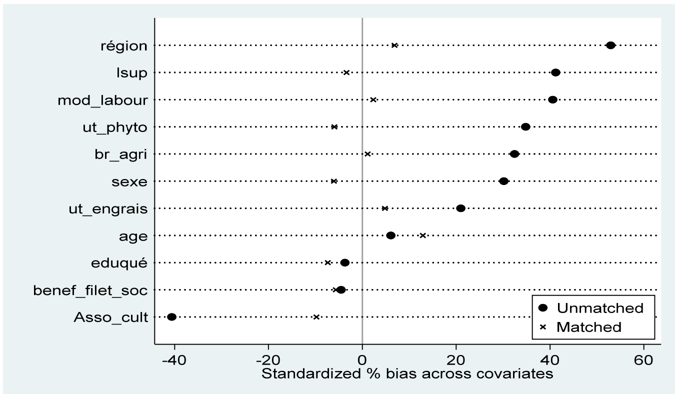

Figure 2: Test on average food expenditure

Matching test on poverty: Figure 3A shows the kernel density curves of the estimated propensity scores for the treatment group (adopters of the improved seed) and the control group (non-adopters of the new technology). Analysis of the results reveals that the distribution of the treatment group is shifted to the right, indicating that those farmers who adopted the improved seed have higher propensity scores than those in the control group. This means that the farmers in the treatment group (adopters) have a higher average probability of income, thus showing a difference between the two groups. Since the two groups differ on the basic covariates, they need to be balanced. The results of the balancing procedure show that the kernel density plots of the improved seed adopters and non-adopters groups overlap almost perfectly (Figure 3B). These plots show that the two groups have been balanced on the basis of propensity scores. Thus, the two groups have the same characteristics, and therefore only the adoption or non-adoption of improved seed is the difference between the two groups.

Table 3. Determinants of improved seed adoption

Explained variables	Propensity score		Marginal effects	
	Coef.	t-stat	Coef.	t-stat
Age	-0.003	(-0.47)	-.0002297	(0.702)
Utilization fertilizer	0.145	(1.01)	0.128797	(0.38)
Gender	0.398**	(2.53)	.0352188**	(0.013)
educated	0.016	(0.11)	.0013888	(0.913)
benef_filet_soc	-0.057	(-0.14)	-.0050462	(0.890)
Log(area)	0.113***	(6.09)	.0100082***	(0.000)
Phytosanitary use	0.581***	(4.01)	.0514331	(0.000)
Agricultural branch	0.731***	(2.82)	.0647142	(0.005)
Region_ Maritime				
Trays	1.468***	(2.78)	.07718***	(0.000)
Central	1.111*	(1.90)	.0492291*	(0.032)
Kara	1.574***	(3.01)	.0870067***	(0.000)
Savannahs	1.616***	(2.97)	.0911206***	(0.000)
Cultural Association	-0.557***	(-3.13)	-.0493415	(0.002)
Plowing mode	0.292	(1.39)	.0258214	(0.151)
The following list is some of the most important issues raised in the last few years.	-4.854***	(-7.42)		
N	2679.000			
r2_p	0.094			
It	-820.875			
p	0.000			

Source: Author based on EHCVM data, 2018-2019

*** significant at the 1% level; ** significant at the 5% level, * significant at the 10% level

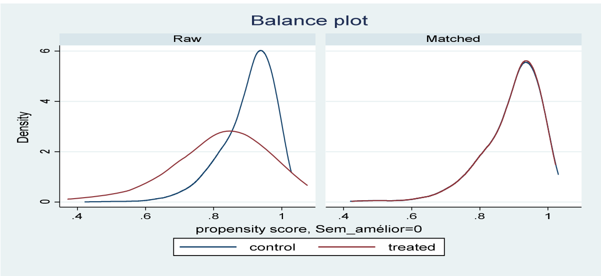

Figure 3A and 3B. Matching test on poverty

Matching test on consumer expenditure: Figure 4A above shows the kernel density curves of the estimated propensity scores for the entire treatment group (adopters of improved seed) and the control group (non-adopters of improved seed). Analysis of the results reveals that the distribution of the treatment group is shifted to the right, indicating that those farmers who adopted improved seeds have higher propensity scores than those in the control group. This means that the farmers in the treatment group (adopters) have a higher average probability of income, thus showing a difference between the two groups. Since the two groups differ on the basic covariates, they need to be balanced. The results of the balancing procedure show that the kernel density plots of the improved seed adopters and non-adopters groups overlap almost perfectly (Figure 4B). These plots show that the two groups have been balanced based on propensity scores. Thus, both groups have the same characteristics, and only the adoption or non-adoption of improved seed differs between the two groups.

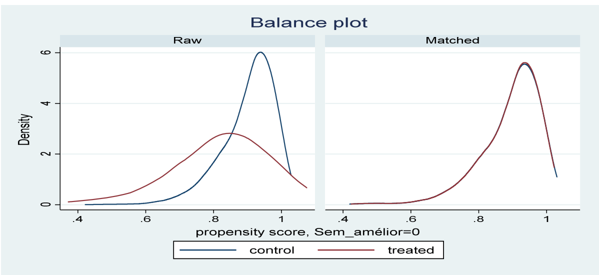

Figure 4A and 4B. Matching test on consumer expenditure

Test on average consumer expenditure: In order to test whether equilibrium is achieved for each of the basic covariates used in the calculation of propensity scores, the test on the matching of the two groups (adopter and non-adopter) was carried out. Thus, Figure 5 presents the standardized mean difference distributions between the treatment and control groups for all covariates before and after matching against the estimated propensity scores. Analysis of the figures reveals a difference in means for most of the covariates close to 0.

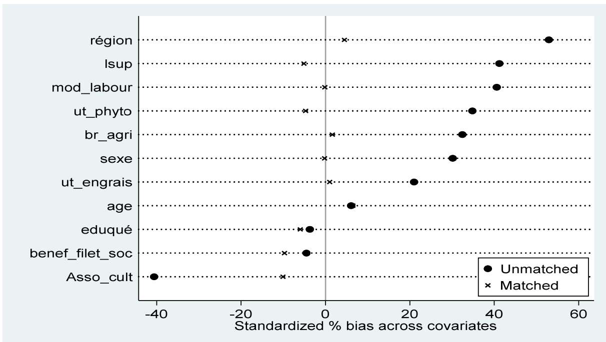

Figure 5. Test on average consumer expenditure

PRESENTATION OF RESULTS

Determinants of improved seed adoption

Table 3, shows that gender, area, use of agrochemicals, agricultural branch, crop association, and region are the determinants of improved seed adoption. On the other hand, age, fertilizer use, education, social safety net, and tillage mode are not determinants of improved seed adoption in this analysis. Among these variables, gender, area, use of agrochemicals, agricultural branch, and region positively affect the adoption of improved seeds. In contrast, crop association negatively affects the adoption of improved seeds. The marginal effects show that gender positively and significantly affects technology adoption at the 5% level. This, means that the probability of men adopting improved seeds is 3.5% compared to women. The use of plant protection products positively and significantly affects the adoption of improved seeds at the 1% threshold. The same is true for the agricultural branch. Compared to the maritime region, the probability of adopting improved seeds decreases from the plateau region to the central region. On the other hand, it increases from the Kara to the savannah. However, the significance of this variable differs. It is 1% except in the central region where it is 10%. With regard to area, it positively affects the adoption of improved seed at the 1% threshold. This means that if the area increases by 1 percentage point, the probability of adopting an improved seed is 0.01. Regarding crop association, it negatively affects the adoption of improved seeds. This means that compared to monoculture, combining crops lowers the probability of adopting improved seeds by 0.04.

Effects of improved seed adoption on food expenditure and poverty

Table 4 shows the estimated average treatment effect on adopters' income, poverty, and food expenditure. The analysis of the results shows that the adoption of improved seeds has a positive and significant effect on income and poverty at the 5% level. On the other hand, the effect on food expenditure is positive and significant at the 10% threshold. Indeed, the results reveal that income can increase by 0.1220 units by adopting improved seeds. As for poverty, the results show that it decreases by 7 points compared to non-adopters. As for food expenditure, it increases by 0.0906 units among adopters. Table 5 shows the estimated average treatment effect on income, poverty, and food expenditure of adopters.

Table 4. Effects on food expenditure and poverty

Variable	Treated	Controls	ATT	H.E.	T-stat
Total Expenditure	284	2395	0.1220**	0.055	2.24
Poverty	284	2395	-7.9225**	3.787	2.09
Food expenditure	284	2395	0.0906*	0.052	1.76

Source: Author based on EHCVM data, 2018-2019
*** significant at the 1% level; ** significant at the 5% level, * significant at the 10% level.

Table 5. Calculation of the ETA

	(2)	(1)	(3)
	Log(total expenditure)	Poverty	ldep_alim
ATE			
r1vs0.Sem_improved	0.169***	-7.391**	0.105**
	(4.12)	(-2.21)	(2.43)

Source: Author based on EHCVM data, 2018-2019
*** significant at the 1% level; ** significant at the 5% level.

The analysis of the results shows that the adoption of improved seeds has a positive and significant effect on income at the 1% level. On the other hand, the effect on food expenditure and poverty is positive and significant at the 5% level. Indeed, the results show that by adopting improved seeds, income can increase by 0.169 percentage points. As for poverty, the results show that it decreases by 7 points compared to non-adopters. As for food expenditure, it increases by 0.105 percentage points among adopters. The analysis of the heterogeneity of the effect of the adoption of new technologies on poverty, in particular on consumption expenditure (Table 6), is done assuming that farmers have a different level of adoption.

Table 6. Quantile regression of improved seed adoption on consumption expenditure

	Log (Total consumption)			
Variables	0.25	0.5	0.75	0.95
	b/t	b/t	b/t	b/t
Sem_improvement	0.102***	0.132**	0.174***	0.044
	(3.53)	(2.30)	(3.54)	(0.92)
Age	-0.000	-0.002**	-0.004***	-0.005***
	(-0.25)	(-2.24)	(-2.85)	(-3.60)
Gender	0.314***	0.275***	0.324***	0.323***
	(8.49)	(9.92)	(10.46)	(4.93)
Ut_fertilizer	0.136***	0.120***	0.098***	0.100**
	(5.68)	(4.51)	(2.73)	(2.49)
Educated	0.198***	0.217***	0.124***	0.071**
	(8.83)	(7.33)	(3.90)	(1.97)
Benef_filet_soc	-0.085***	-0.019	-0.110**	-0.217***
	(-3.00)	(-0.27)	(-2.15)	(-2.91)
Ut_phyto	0.056**	0.043	0.004	0.188***
	(2.40)	(1.60)	(0.11)	(4.28)
Region (Ref. Maritime)				
Trays	-0.114***	-0.173***	-0.264***	-0.271***
	(-2.60)	(-4.13)	(-4.78)	(-2.97)
Central	-0.005	0.169***	0.147	0.219***
	(-0.10)	(2.68)	(1.60)	(3.50)
Kara	-0.392***	-0.323***	-0.249***	-0.256***
	(-8.42)	(-9.01)	(-4.26)	(-3.71)
Savannah	-0.366***	-0.349***	-0.367***	-0.129
	(-8.15)	(-6.67)	(-4.55)	(-1.48)
Asso_cult	-0.043*	-0.094***	-0.081**	-0.000
	(-1.75)	(-3.22)	(-2.47)	(-0.00)
Mod_labour	-0.007	0.009	0.123*	-0.114**
	(-0.21)	(0.19)	(1.86)	(-2.32)
lsup	-0.017***	-0.023***	-0.027***	-0.007
	(-3.49)	(-4.59)	(-4.81)	(-1.16)
typ_sol	0.068***	0.050***	0.021	-0.044***
	(6.34)	(4.74)	(1.47)	(-3.05)
fertility_level	0.088***	0.046***	0.044**	-0.017
	(5.97)	(2.79)	(2.57)	(-0.67)
The following list is some of the most important issues raised in the last few years.	13.052***	13.555***	14.052***	14.819***
	(185.26)	(231.76)	(173.49)	(153.61)
r2_p	0.1013	0.0810	0.0620	0.0582
N	2679.000	2679.000	2679.000	2679.000

Source: Author based on data from EHCVM, 2018-2019 (INSEED, 2018)
*** significant at the 1% level; ** significant at the 5% level.

Considering the farmer heterogeneity in their expenditure, it is necessary to run a quantile regression to analyze the effect of adopting new technologies on consumption expenditure. The results of the first three quantiles show that adopting new technologies (improved seeds) is positive and significant. Indeed, a 1% increase in the adoption of improved seeds increases consumption expenditure by 0.102%; 0.132%, and 0.174%, respectively, at the 1st, second, and third quantiles. Shiferaw et al. (2011) argue that adopting improved wheat varieties increases food security and that adopting farm households would have benefited significantly if they had adopted new varieties. Their results show adopters increased their food consumption expenditure by 2.7 to 4.5 percentage points. As a policy, they suggest vital investments in agricultural research for key staple foods widely consumed by the poor and efforts to improve access to modern varieties and services to ensure food security in Ethiopia. These results corroborate those of Manda et al. (2019) and Klasen et al (2013). For the former, adopting improved cowpea varieties in Nigeria increases household income per capita and asset ownership by 17 and 24 percentage points (Manda, *et al.,* 2019). For the latter, Indonesian farm households that adopt new cash crop varieties achieve about 14% higher income than non-adopters. Furthermore, technology adoption significantly increases household consumption expenditure per adult from USD 53.98 to 57.89 and reduces the incidence of poverty from 17.4 to 18.2 percent (Shita, Kumar, & Singh, 2021).

Conclusion

This paper starts from the premise that the adoption of new technologies has contributed to poverty reduction in Togo. The results of the two methods show that adopting new technologies is significant and has a positive effect on consumption expenditure and poverty. The results obtained for the two methods used are almost identical. They reveal that by adopting improved seeds, income can increase by 0.169 percentage points, and poverty decreases by 7 points compared to non-adopters. Food expenditure increases by 0.105 percentage points among adopters. Intensifying the adoption of new agricultural technologies, and significantly improving the adoption of improved seeds, is relevant and essential for reducing rural poverty in Togo and, indirectly, poverty among non-farming households at the national level. Therefore, a revival of investment in agricultural research and development and the growth and adoption of new knowledge (technology) could contribute to substantial gains in agricultural productivity and income.

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