The Impact of Agricultural Technology Adoption on Poverty: The case of NERICA rice varieties in Benin

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Abstract:

This study examines the relationship between agricultural technology adoption and poverty with a focus on New Rice varieties for Africa (NERICA). The NERICAs are a group of rice varieties developed by the Africa Rice Centre during the 1990s, resulting from the inter-specific crosses between the *Oryza sativa* high yielding rice species from Asia and the locally adapted and multiple-stress resistant *Oryza glaberrima* African rice species.They are believed to provide great hope for African agriculture. Introduced in Benin in 1998, there has been no published analysis on the impact of their adoption by farmers.

The paper uses the counterfactual outcomes framework of modern evaluation theory to estimate the *Local Average Treatment Effect* (LATE) of NERICA adoption on household expenditure among 268 households from rural Benin. Results indicate that the adoption of NERICA varieties has a positive and significant impact on household expenditure. Furthermore, the impact is higher among female-headed households (161.75 FCFA/day) than male-headed households (128.34 FCFA/day). The findings suggest that there is a scope for reducing poverty through the accelerated adoption of NERICA varieties by farmers.

Key words: NERICA, Poverty, Agricultural technology, Impact assessment, Local Average Treatment Effect, Benin

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1 Introduction

Poverty is the main development problem confronting the world and agricultural growth is seen as a best-bet strategy for poverty reduction. Indeed, agriculture is central to the livelihood of most people that live in rural areas whose population accounts for more than half of the world's population. Productivity increases in agriculture can reduce poverty by increasing farmers' income, reducing food prices and thereby, enhancing increments in consumption. In DFID (2003) it is estimated that a 1 percent increase in agricultural productivity reduces the percentage of poor people living on less than 1 dollar a day by between 0.6 and 2 percent and no other economic activity generates the same benefit for the poor.

The adoption of new agricultural technology such as the high yielding varieties (HYV) that led to the green revolution in Asia could lead to significant increases in agricultural productivity in Africa and stimulate the transition from low productivity subsistence agriculture to a high productivity agro-industrial economy (World Bank, 2008). Mendola (2006) observes that the adoption of HYV has a positive effect on household wellbeing in Bangladesh. More recently, Kijima et al (2008) conducted a study on the impact of NERICA in Uganda and found that NERICA adoption reduces poverty without deteriorating the income distribution. Other studies that show a positive impact of adoption of agricultural technologies include; Winters et al. (1998) and deJanvry and Sadoulet (1992). In contrast, a study in Bangladesh by Hossain *et al* (2003) shows that the adoption of HYV of rice has a positive effect on the richer households but had a negative effect on the poor. In Zimbabwe, Bourdillon et al (2002) observe that the adoption of HYV of maize increases the crop incomes of adopters only modestly. These conflicting findings justify the need for further research on this topic.

We note, however, that most studies have assessed the impact of technology adoption by simply examining the differences in mean outcomes of adopters and non-adopters or by using simple regression procedures that include the adoption status variables among the set of explanatory variables. Critics have pointed out that such simple procedures are flawed because they fail to deal appropriately with the self-selection bias in observational data collected through household surveys (Rubin, 1974; Rosembaum and Rubin, 1983; Rosembaum, 2002; Heckman and Vytlacil, 2005; Lee, 2005) hence they fail to identify the causal effect of adoption.

There is a rapidly growing literature evaluating the impact of anti- poverty programs in using experimental and non-experimental methods that deal appropriately with the self-selection problems (Ravallion, 2006; Todd, 2006;). However, few of these studies have focused on assessing the impact of technology adoption on rural poverty. Notable exceptions include a study by Mendola (2006) on the impact of technology adoption on poverty in Bangladesh who uses the propensity-score matching (PSM) method to deal with the self-selection bias problem and estimates the *average treatment effect (ATE)* of adoption of high yielding rice varieties on income. However, by only controlling for the *observable* covariates that are partly responsible for the farmer self-selection into the adoption state the PSM only removes the part of the selection bias called "overt bias" (Lee, 2005; Rosenbaum, 2002). PSM cannot remove what is called "*hidden bias*" which is caused by the *unobservable* covariates that may also affect the farmer self-selection into the adoption state and the outcomes indicators (Heckman and Vytlacil, 2005; Rosenbaum, 2002). Furthermore, when treatment is endogenous (as in the adoption case), we are faced with the *non-compliance* problem whereby subjects may not stick to their assigned groups even if assignment to the treatment and controlled groups were to be done randomly as in controlled social experiments (Imbens and Rubin 1997; Heckman, 1996; Angrist et. al, 1996; Imbens and Angrist, 1994). In the adoption context, *noncompliance* means that there are farmers who will never adopt a technology even when they have free access to it. In this context, the ATE parameter estimated with the PSM method does not identify the causal effect of adoption. Instead, in the presence of non-compliance ATE identifies what is defined in the evaluation literature as the *intention-to-treat effect* (ITT) which in the adoption context can be interpreted as the "supply-of-the technology" effect (i.e. the impact of supplying a technology to farmers). The impact parameter that identifies the causal effect of adoption in the presence of *non-compliance* is the *local average treatment effect* (LATE) introduced by Imbens and Angrist (1994), which restrict the computation of the average treatment effect to the subpopulation of "*compliers*". In the adoption context the subpopulation of compliers correspond to that of potential adopters of the technology. In this paper we use the *local Average treatment effect* (LATE) framework to estimate the causal effect of technology adoption poverty focusing on the case of the NERICA rice in Benin and on household consumption expenditure as an indicator of the poverty status.

The paper is organized as follows. Section 2 presents the econometric framework for assessing the impact of agricultural technology adoption on household outcomes. Section 3 describes the empirical context of the study, sampling methodology and the data. The data and descriptive statistics are presented in section 4. The results and discussions on the impact of NERICA adoption on household expenditure are presented in Section 5, while the conclusions and policy implications of the findings are presented in Section 6.

2. The econometric framework

Under the potential outcome framework developed by Rubin (1974), each farm household has ex-ante two potential outcomes: an outcome when adopting a NERICA variety that we denote by y_1 and an outcome when not adopting a NERICA variety that we denote by y_0.[1] Letting the binary outcome variable d stand for NERICA adoption status with d =1 meaning adoption and d =0 non-adoption, we can write the *observed* outcome y of any farm household as a function of the two potential outcomes: $y = dy_1 + (1-d)y_0$. For any household the causal effect of the adoption on its observed outcome y is simply the difference of its two potential outcomes: $y_1 - y_0$. But, because the realizations of the two potential outcomes are mutually exclusive for any household (i.e. only one of the two can be observed ex-post), it is impossible to measure the individual effect of adoption on any given household. However, one can estimate the mean effect of adoption on a population of households: $E(y_1 - y_0)$, where E is the mathematical expectation operator. Such a population

[1] The outcome analyzed in the empirical section is the are consumption expenditure, which we take as one of the poverty indicators.

parameter is called the average treatment effect (ATE) in the literature. One can also estimate the mean effect of adoption on the subpopulation of adopters: $E(y_1\text{-}y_0 \mid d=1)$, which is called the average treatment effect on the treated and is usually denoted by ATE1 (or ATT). The average treatment effect on the *untreated*: $E(y_1\text{-}y_0 \mid d=0)$ denoted by ATE0 is also another population parameter that can be defined and estimated.

The methods proposed to minimize the effects of overt and hidden biases and deal with the problem of *non-compliance* can be classified under two broad categories. (see Imbens 2004). First, there are the methods designed to remove overt bias only and which are based on the conditional independence assumption (Rubin, 1974; Rosenbaum and Rubin, 1983) which postulates the existence of a set of observed covariates ***x***, which, when controlled for, renders the treatment status d independent of the two potential outcomes y_1 and y_0. The estimators using the conditional independence assumption are either a pure parametric regression-based method where the covariates are possibly interacted with treatment status variable to account for heterogeneous responses, or they are based on a two-stage estimation procedure where the conditional probability of treatment $P(d=1 \mid x) \equiv P(x)$, called the *propensity score*, is estimated in the first stage and ATE, ATE1 and ATE0 are estimated in the second stage by parametric regression-based methods or by non-parametric methods, which include various matching method estimators that include the ones used by Mendola (2006).[2] In this paper, the conditional independence based estimators of ATE, ATE1 and ATE0 we used are the so-called inverse propensity score weighing estimators (IPSW), which are given by the following formulas (see Imbens, 2004; Lee 2005, pp 65-69)

$$\hat{ATE} = \frac{1}{n}\sum_{i=1}^{n}\frac{(d_i - \hat{p}(x_i))y_i}{\hat{p}(x_i)(1-\hat{p}(x_i))} \quad \textbf{(1)}$$

$$\hat{ATE}1 = \frac{1}{n_1}\sum_{i=1}^{n}\frac{(d_i - \hat{p}(x_i))y_i}{(1-\hat{p}(x_i))} \quad \textbf{(2)}$$

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[2] The propensity score-based estimators exploit the fact that the conditional independence assumption implies the independence of *w* and of the potential outcomes y_1 and y_0 conditional on $P(x)$ as well (Rosenbaum and Rubin, 1983). They also use the additional assumption that $0 < P(x) < 1$.

$$A\hat{T}E0 = \frac{1}{1-n_1}\sum_{i=1}^{n}\frac{(d_i - \hat{p}(x_i))y_i}{\hat{p}(x_i)} \quad \textbf{(3)}$$

Where n is the sample size, $n_1 = \sum_{i=1}^{n} d_i$ is the number of treated (i.e. the number of Nerica adopters) and $\hat{p}(x)$ is a consistent estimate of the propensity score evaluated at $\boldsymbol{x}$. We use a probit specification to estimate the propensity score.

Second, there are the *instrumental variable* (IV) based methods (Heckman and Vytlacil, 2005; Imbens 2004; Abadie, 2003; Imbens and Angrist, 1994) which are designed to remove both overt and hidden biases and deal with the problem of endogenous treatment. The IV based methods assumes the existence of at least one variable **z** called *instrument* that explains treatment status but is redundant in explaining the outcomes y_1 and y_0, once the effects of the covariates $\boldsymbol{x}$ are controlled for. Different IV based estimators are available depending on functional form assumptions and assumptions regarding the instrument and the unobserved heterogeneities. In this paper we use two IV-based estimators to estimate the LATE of adoption of Nerica on household expenditure. The first one is the simple non-parametric Wald estimator proposed by Imbens and Angrist, (1994) and which require only the observed outcome variable y, the treatment status variable d and an instrument z. The second IV estimator is Abadie's (2003) generalization of the LATE estimator of Imbens and Angrist (1994) to cases where the instrument z is not totally independent of the potential outcomes y_1 and y_0; but will become so conditional on some vector of covariates $\boldsymbol{x}$ that determine the observed outcome y.

To give the expressions of the Imbens and Angrist (1994) LATE estimator and that of Abidie (2003), we note that the exposure to the Nerica status variable is a "natural" instrument for the adoption status variable (which is the treatment variable here). Indeed, firstly one cannot adopt a Nerica without being exposed to it and we do observe some farmers adopting Nerica (i.e. exposure does cause adoption). Second, it is natural to assume that exposure to Nerica affects overall household expenditure/income only through adoption (i.e. the mere exposure to the Nerica without adoption does not affect the ependiture/income of a farmer). Hence, the two requirements for the exposure status variable to be a valid instrument are met. Now, let z be a binary outcome variable taking the value 1 when a farmer is *exposed* to the Nerica and the value 0 otherwise. Let d_1 and d_0 be the binary variables designating the two potential *adoption* outcomes status of the farmer with and without exposure to the Nericas, respectively (with 1 indicating adoption and 0 otherwise). Because one cannot adopt a Nerica without being exposed to it, we have d_0=0 for all farmers and the *observed* adoption outcome is given by $d=zd_1$. Thus, the subpopulation of potential adopters is described by the condition d_1=1 and that of actual adopters is described by the condition d=1 (which is equivalent to the condition z=1 and d_1=1). Now, if we assume that z is independent of the potential outcomes d_1, y_1 and y_0 (an assumption equivalent to assuming that exposure to Nerica is random in the population), then the mean impact of Nerica adoption on the average expenditure/income of the subpopulation of Nerica potential adopters (i.e. the LATE) is given by (Imbens and Angrist, 1994; Imbens and Rubin 1997, Lee, 2005):

$$E(y_1 - y_0 \mid d_1 = 1) = \frac{E(y \mid z=1) - E(y \mid z=0)}{E(d \mid z=1) - E(d \mid z=0)} \quad \textbf{(4)}$$

The right hand side of (4) can be estimated by its sample analogue:

$$\left(\frac{\sum_{i=1}^{n} y_i z_i}{\sum_{i=1}^{n} z_i} - \frac{\sum_{i=1}^{n} y_i (1-z_i)}{\sum_{i=1}^{n} (1-z_i)} \right) \times \left(\frac{\sum_{i=1}^{n} d_i z_i}{\sum_{i=1}^{n} z_i} - \frac{\sum_{i=1}^{n} d_i (1-z_i)}{\sum_{i=1}^{n} (1-z_i)} \right)^{-1} \quad \textbf{(5)}$$

which is the well known *Wald* estimator.[3]

The assumption that exposure to the Nerica varieties is random in the population is unrealistic . We therefore use Abadie's LATE estimator which does not require the assumption but instead requires the much weaker conditional independence assumption: The instrument z is independent of the potential outcomes d_1, y_1 and y_0 conditional on a vector of covariates $\boldsymbol{x}$ determining the observed outcome y.[4] With these assumptions, the following results can be shown

[3] In our application we have used the equivalent IV estimation procedure in Stata which provides the standard error of the estimate directly.

[4] For completeness, it is also assumed that the conditional probability of Nerica exposure $P(\mathrm{d}=1 \mid x)$ is strictly between zero and 1 and that of Nerica potential adoption $P(d_1=1 \mid x)$ strictly positive for all values of x.

to hold for the conditional mean expenditure response function for potential adopters $f(x,d) \equiv E(y \mid x, d; d_1=1)$ and any function g of (y,x,d) (see, Abadie, 2003; Lee 2005):

$$f(x,1) - f(x,0) = E(y_1 - y_0 \mid x, d_1 = 1) \quad \textbf{(6)}$$

$$E(g(y,d,x) \mid d_1 = 1) = \frac{1}{P(d_1 = 1)} E(\kappa \cdot g(y,d,x)) \quad \textbf{(7)}$$

Where $\kappa = 1 - \frac{z}{p(z=1 \mid x)}(1-d)$ is a weight function that takes the value 1 for a potential adopter and a negative value otherwise. The function $f(x,d)$ is called a *local Average reponse function (LARF)* by Abadie (2003). Estimation proceeds by a parameterization of the LARF $f(\theta; x, d) = \mathrm{E}(y \mid x, d; d_1=1)$. Then, using equation 2 with $g(y,d,x) = (y - f(\theta; x,d))^2$, the parameter θ is estimated by a weighted least squares scheme that minimizes the sample analogue of $E\{\kappa(y - f(\theta; x,d))^2\}$. The conditional probability $P(z=1|x)$ appearing in the weight κ is estimated by a probit model in a first stage. Abadie (2003) proves that the resulting estimator of θ is consistent and asymptotically normal. Once, θ is estimated, equation (6) is used to recover the conditional mean treatment effect $E(y_1 - y_0 \mid x, d_1 = 1)$ as a function of x. The LATE is then obtained by averaging across x using equation (7). For example, with a simple linear function $f(\theta,d,x) = \alpha_0 + \alpha d + \beta x$ where $\theta=(\alpha_0, \alpha, \beta)$; then $E(y_1 - y_0 \mid x, d_1 = 1) = \alpha$. In this case, there is no need for averaging to obtain the LATE, which is here equal to α. Hence, a simple linear functional form for the LARF with no interaction between d and x implies a constant treatment effect across the subpopulation of potential adopters. In the estimation below, we postulate an exponential conditional mean expenditure response function with and without interaction to guaranty both the positivity of predicted expenditure and heterogeneity of the treatment effect across the subpopulation of Nerica potential adopters. Because of the fact that exposure is a necessary condition for adoption, it can be shown that the LATE for the subpopulation of potential adopters (i.e. those with d_1=1) is the same as the LATE for the subpopulation of *actual* adopters (i.e. those with $d=zd_1$=1).[5]

4. Data and descriptive statistics

The NERICA rice varieties are the result of inter-specific crosses between the *Oryza sativa* high yielding rice species from Asia and the locally adapted and multiple-stress resistant *Oryza glaberrima* African rice species (Jones et al. 1997) and were first introduced in Benin in 1998. Adoption studies conducted in 2004 show a NERICA sample adoption rate of 18% and an estimated potential population adoption rate of 50% (Adégbola et al., 2005).

Data were collected through a household survey conducted in 2004 by the Africa Rice Centre from the Collines region of Benin. The data collected pertain to the 2004 cropping season, and were collected from 268 rice farmers in 24 villages. The study area included 12 villages where the Africa Rice Centre had been conducting on-farm trials and Participatory Varietal Selection (PVS) activities on NERICA varieties since 1997, and 12 non NERICA villages within 5 to 10 kilometres radius from the villages hosting research. At least ten households were randomly selected in each village leading to a total sample size of 268 farmers. The data were collected on socio-economic characteristics, farmer knowledge of varieties and the varieties cultivated since 2000, quantities of inputs, revenue from crops and non-farm activities and household expenditure. Table 1 reports statistics for selected variables for sample farmers. Results on expenditure indicate that an adult man in a NERICA adopting household spends on average 72.41 FCAs per day more than an adult man in a non-adopting household. The difference in household expenditure between these two groups is statistically different from 0 at the 1% level. Based on the rural poverty line for Benin of 51413 CFAs per capita per annum, 42% of the sample farmers are poor. More non- adopters (47%)

[5] This result is a general result that holds whenever the condition d_0=0 is satisfied (see, Abadie, 2003 or Imbens and Rubin 1997).

than NERICA adopters (22%) are poor. However, based on the observed differences one can not tell whether the differences are solely due to NERICA adoption.

5.0 Results and discussion

The impact of technology adoption on poverty was evaluated using the overall household expenditure[6], which also provides an indication of the degree of poverty of the household. Since adoption is an endogenous variable, we are faced with the *non-compliance* problem. We thus, consistently estimate the impact of NERICA adoption on expenditure using the *local average treatment effect* (LATE) which corrects for the problem of *non- compliance* and the we compare the results with other estimation methods; the prospensity score matching method and the parametric and semi-parametric ATE methods that do not correct for *non- compliance*.

Results of the impact of NERICA varieties adoption on expenditure are presented in Table 2. Column 4 and 5 present results of the LATE effect of NERICA varieties on household per capita expenditure, estimated by the Wald estimator proposed by Imbens and Angrist (1994) and the Instrumental Variable estimator proposed by Abadie (2003), respectively. The results based on Abadie's IV estimator (column 5) indicate that NERICA adoption positively and significantly increases expenditure by 147.51 FCFA per day per person. The results further indicate that the IV estimator (column 5) is much larger in magnitude and highly significant [147.51CFA (se=48.69)], than the Wald estimator (column 4) [100.71 CFA (se=206.6)]. The impact of NERICA adoption on expenditure is significantly higher among households headed by women (161.75 FCFA/day) compared to 128.34 FCFA/day for households headed by men.

Consistent with prior expectation, the ATE estimate based on the propensity score matching method (column 1), is smaller in magnitude and less significant [94.91CFA (se=25.5)] than the LATE based on IV estimate in column 5. The estimate based on the Inverse Propensity Score

[6] Household expenditure level is usually considered to be the best way of measuring household economic status, rather than revenue, since revenue varies considerably and measuring it is subject to error.

Weighting (IPSW) in column 2 is also smaller in magnitude and only marginally significant [60.2 CFA (se=33.88)]. The estimate based on parametric ATE (column 3) is also smaller than the LATE estimate based on the IV method in column 5. The results from PSM and ATE methods are also less plausible because they are based on a compromising approach which assumes the absence of *non-compliance*.

The increase in productivity of rice farmers, following the adoption of NERICA varieties (Adégbola *et al*., 2005) possibly explains these results given that the lack of sufficient and reliable revenue is at the heart of food insecurity, and the incapacity to procure sustainable means of self sufficiency. These results suggest that the promotion of NERICA cultivation can contribute to improving expenditure/income of farmers and consequently to poverty reduction and are consistent with those of Irz *et al*. (2001), who shows that a close relationship exists between farm productivity and household poverty.

6 Conclusions

The NERICA varieties were developed with the aim of contributing to poverty reduction and improving food security through increased productivity of rice. This paper provides an ex- post assessment of NERICA rice varieties adoption on poverty. A counterfactual outcome framework of modern evaluation theory is used to consistently estimate NERICA adoption impact on household expenditure and results indicated that the adoption of NERICA varieties has had a positive and significant effect on household expenditure. The impact is found to be higher among women than men. The findings suggest that adoption of NERICA rice varieties is associated with poverty reduction and that there is a great scope for reducing poverty by promoting the cultivation of NERICA varieties in regions with high good climatic conditions for NERICA cultivation.

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Table 1: Demographic and socio economic characteristics of adopters and non-adopters

Socio economic Characteristic	Non-adopters (n=218 ~81%)	Adopters (n=50~19%)	Total (268)
Average area for rice farms (ha)	0.32 (0.34)	0.43 (0.39) ***	0.34 (0.36)
Average age of farmer	42 (13,07)	43 (11,07)	43 (12.40)
Average family size	5.7 (2.78)	7.2 (2.88) ***	5.99 (2.87)
Proportion of farmers with formal education	32	32	32
Proportion of farmers with contact with institutions	62	70	64
Proportion resident in PVS village	44	74***	50
Proportion participating PVS trials	38	54**	41
Household expenditure per equivalent adult (FCFA/day)			**Difference**
Total sample	206.89 (89.07)	279.31*** (107.15)	72.42
Women	219.33 (93.06)	287.25 *** (98.72)	67.92
Men	187.50 (79.16)	268.35*** (119.44)	80.85
Poverty measures			**Total**
Poverty head count index (%)	47.2	22	42.4
Poverty gap	13.8	4.12	12

*** and **=means significantly different at 1% and 5%, respectively
Source: WARDA- 2004, NERICA Impact Study

Table 2: The impact of Nerica adoption on expenditure (CFAs)- based on five estimation methods

PRAMETERS	PROPENSITY SCORE MATCHING (1)	ATE (IPSW) (2)	ATE -(EXPON ENTIAL) (3)	LATE – WALD (4)	LATE (EXPON ENTIAL) (5)
ATE/LATE		60.20 (33.88)*	107.36 (16.14)***	100.71 (206.6)***	147,51 (48,69)***
ATE1	94.91 (25.5)**	90.07 (22.04)***	88.16 (13.72)***		
ATE0		53.26 (39.48)	111.8 (17.4)***		
PSB		29.87 (29.92)	-19.20 (9.37)**		
Impact by gender					
Men					128,34 (45,15)***
Women					161,75 (68,48)**

*** and **=means significantly different at 1% and 5%, and 10% levels, respectively

Source: WARDA- 2004, NERICA Impact Study