Impact of Improved Rice Technology (NERICA varieties) on Income and Poverty among Rice Farming Households in Nigeria: A Local Average Treatment Effect (LATE) Approach

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Abstract

This study examines the impact of the adoption of New Rice for Africa varieties (NERICAs) on income and poverty among Nigerian rice farming households. It used instrumental variables estimators to estimate the Local Average Treatment Effect (LATE) of adopting NERICA on income and poverty reduction, using the cross-sectional data of 481 farmers from the upland, lowland and irrigated rice ecologies The findings reveal a robust, positive and significant impact of NERICA variety adoption on farm household income and welfare measured by per capita expenditure and poverty reduction. The empirical results suggest that adoption of NERICA varieties helped raise household per capita expenditure and income by averages of 49.1% and 46.0%, respectively, thereby reducing the probability of adoptive households falling below the poverty line. The study suggests that increased investment in NERICA dissemination, with complementary measures, is a reasonable policy instrument to raise incomes and reduce poverty among rice farming households.

Keywords: impact, NERICA varieties, income, poverty, local average treatment effect, Nigeria
JEL: C13, O33, Q12, Q16

1 Introduction

Agricultural growth is essential for fostering economic development and feeding growing populations in most less developed countries. Area expansion and irrigation have already become a minimal source of output growth at a world scale. Agricultural growth will depend more and more on yield-enhancing technological change (DATT and RAVALLION, 1996; HOSSAIN, 1989). It is believed the adoption of new agricultural technology, such as the high yielding varieties that kick-started 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). In this regard, MENDOLA (2007) observes that the adoption of high yielding varieties has had a positive effect on household well-being in Bangladesh. In addition, empirical studies show that gains from new agricultural technology influenced the poor directly, by raising incomes of farm households and, indirectly, by raising the employment and wage rates of functionally landless laborers, and by lowering the price of food staples (PINSTRUP-ANDERSEN et al., 1976; HOSSAIN et al., 1994; WINTERS et al., 1998; DE JANVRY and SADOULET, 1992, 2002; IRZ et al., 2002; BELLON et al., 2006; BINSWANGER and VON BRAUN, 1991; EVENSON and GOLLIN, 2003; JUST and ZILBERMAN, 1988; DIAGNE et al., 2009).

In recent years, rice production has been expanding at the rate of 6% per annum in Nigeria, with 70% of the production increase due mainly to land expansion and only 30% being attributed to an increase in productivity (FAGADE, 2000; FALUSI, 1997; AFRICA RICE CENTER (WARDA), 2007 and 2008; OKORUWA et al., 2007). Notwithstanding, the demand for rice is growing faster than production in the country, thus making the country dependent on imported rice to meet the high demand. The persistence of a demand and supply gap has been attributed to several factors, prominent among which is the fact that nearly half of Nigeria's 140 million people live below the poverty line (WORLD DEVELOPMENT INDICATORS, 2004; NBS, 2008); together with the lack of high yielding varieties with good grain qualities, competition with imported rice, and inadequate post-harvest processing. Other factors are land degradation and inadequate land preparation, unreliable and uneven rainfall distribution, problems of weeds, insect pests, diseases, birds and lack of training for key stakeholders.

New Rice for Africa (NERICA) varieties are interspecific hybrids between the local African rice (*Oryza glaberrima)* and the Asian rice (*Oryza sativa*) that offer new opportunities for rice farmers, particularly in Nigeria. NERICA varieties have unique characteristics, such as shorter duration (maturing between 30 and 50 days earlier than traditional varieties), higher yield, tolerance to major stresses, higher protein and good taste compared with the traditional rice varieties (JONES et al., 1997; DINGKUHN et al., 1998; AUDEBERT et al., 1998; JOHNSON et al., 1998; DINGKUHN et al., 1999; WOPEREIS et al., 2008) which Nigeria could use in bridging the demand and supply gap in rice. These varieties have also been reported to have stable yields under different management conditions and their introduction to farmers' fields was considered as a first step towards stabilization and sustainable intensification of Africa's fragile production of upland rice. These varieties were introduced on a trial basis to all West African countries, including Nigeria, in 1998 and have been enthusiastically adopted (AFRICA RICE CENTER (WARDA), 2005).

Although government has implemented several development initiatives (African Rice Initiative of 2002; PRESIDENTIAL INITIATIVE on increased rice production of 2005; etc.), there have also been an increasing number of recent requests by government, aid donors and the development community at large for hard evidence to be supplied on the impact of such public programs that claim to reduce poverty. Among the questions often asked and for which answers are being sought are: do the various initiatives really work? How much impact do they have? Previous research trying to address such questions produced 'evaluations', which are now widely seen as unsatisfactory as they provide only qualitative insight and do not assess outcomes against explicit and policy-relevant counterfactuals (RAVALLION, 2005). A few studies carried out after the introduction of NERICA varieties consider the rice sub-sector as a whole but in general terms (OKORUWA et al., 2007; DARAMOLA, 2005; BELLO, 2004; AKANDE, 2001), while SPENCER et al. (2006) focused on the adoption of NERICA varieties only. There is, therefore, an earlier study assessing the impact of NERICA adoption in Nigeria but this new study addresses the empirical questions of whether the NERICA varieties are contributing to income increase and reduction in poverty.

2 Framework of the Study

2.1 Impact Framework

We adopt the livelihood framework approach developed by DFID (2001), which is based on evolved thinking about poverty reduction, the way the poor and vulnerable live their lives and the importance of structural and institutional issues. The approach suggests development activities that are people-centered, responsive and participatory, multilevel, conducted in partnership with both the public and private sectors, dynamic and sustainable. The framework recognizes that every household and community has resources on which to build and support both individuals and the community in acquiring assets needed for their long-term well-being. The framework is quite attractive in the sense that it provides a simple but well-developed way of thinking about a complex issue (welfare). It is also attractive because it can be applied at various levels of detail as a broad conceptual framework or as a practical tool for designing programs and evaluation strategies.

As in every society, individual households in Nigeria are endowed with infrastructure (road, electricity, markets, etc.) and resources comprising natural (land, water, wildlife, etc.), human (skills, aptitudes, knowledge, etc.), financial, physical and social capital (savings, networks, trust, etc.), which constitute the resource constraint based on which they maximize their well-being. These resources are affected by exogenous factors such as agro-climatic conditions (drought, rainfall, etc.), insect pests and diseases which hinder their productivity. Change in technology wrought through the development of improved varieties such as the NERICA varieties with better characteristics (drought tolerance, high yield, weed competitiveness, etc.), and their dissemination through the participatory varietal selection process affect the rice farmers' perception, beliefs expectations and preference toward different rice varieties and inputs used in production. This is because, based on the characteristics of the NERICA varieties and demonstrations within participatory varietal selection, farmers believe that adoption of NERICA varieties would increase their yield and therefore they anticipate strong benefit. This constitutes the farmers' 'value formation' that in turn will condition their decisions in term of investment, crop and varietal choices, and resource allocation to various inputs. Their decisions have to change because the new variety may need different types of inputs compared to those previously used. This can be expected to affect their consumption, marketing of harvested quantities of different crop varieties, savings and income generation activities. Therefore, household decisions and choice constitute the farmers' behavioral outcomes, which will finally affect their income and poverty levels (welfare outcomes). In this paper we investigate whether adopting new rice technology causes resource-poor farmers to improve their incomes and decreases their propensity to fall below the poverty line.

The packaged nature of new agricultural technology makes the evaluation of its welfare effects quite difficult. Many of the studies on the impact of agricultural technology on farm incomes and poverty have usually relied on fairly macro approaches (see, for example, EVENSON and GOLLIN, 2003). On the other hand, many micro-level studies have assessed the impact of technology adoption simply by 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 caused by selection on observables or unobservables present in observational data collected through household surveys. For that reason, these studies fail to identify the causal effect of adoption (IMBENS and WOOLDRIDGE, 2009; HECKMAN and VYTLACIL, 2005; LEE, 2005; IMBENS, 2004; ROSENBAUM, 2002; HECKMAN and ROBB, 1985; ROSENBAUM and RUBIN, 1983; RUBIN, 1974). Thus, the literature appears to document overall positive impacts, with far less evidence at the individual household level that specifically show the effects of the adoption of agricultural technologies on farm income and household poverty level.

Among the studies at the micro-level that have attempted to deal with the problem of self-selection bias are MORRIS (2002), KARANJA et al. (2003), MENDOLA (2007), MOJO et al. (2007) and JAVIER and AWUDU (2010). Some of these studies used the propensity score matching (PSM) method to deal with the self-selection bias problem and estimate the Average Treatment Effect *(*ATE*)* of adoption of high yielding varieties on income (MENDOLA, 2007; MOJO et al., 2007 and JAVIER and AWUDU, 2010). Some of them combine the PSM with double difference methods (ONI et al., 2007; MKONYA et al., 2007). However, the propensity score matching method fails to deal appropriately with the problem of selection on unobservables, which may be handled by the double-difference approach if the unobservables are time invariant. Moreover, neither of the two approaches deals appropriately with the problem of non-compliance.

In order to assess the impact of improved technology adoption on livelihoods, the choice of the appropriate approach to use for identification and estimation of impact depends on how the treatment (i.e. the technology) is disseminated and received by the intended beneficiaries. In this study, the PVS used to disseminate NERICA varieties in Nigeria was implemented in only a few selected states and villages (SPENCER et al., 2006). This means that the overall population of Nigerian rice farmers was not equally exposed to the new varieties (the instrument for the policy intervention was not randomly distributed). On the other hand, rice farmers exposed to the new variety had full control over their decision to adopt or not to adopt (i.e. the receipt of the treatment is endogenous). According to the impact assessment literature, the most plausible assumption to make in this case is that of selection on the unobservable (IMBENS and WOOLDRIDGE, 2009; DIAGNE et al., 2009). This is because farmers decide to adopt NERICA varieties based on the anticipated benefit they would derive by adopting NERICA and this anticipated benefit cannot be observed. Hence, to identify and estimate the impact of NERICA adoption, we need an instrument that is independent of this unobserved anticipated benefit and can affect productivity, income and poverty only through the act of adoption.

2.2 Analytical Framework

2.2.1 The Local Average Treatment Effect (LATE)

There is an expanding theoretical and empirical literature on models where the impacts of discrete (usually binary) treatments are heterogeneous in the population (see ROY, 1951; BJORKLUND and MOFFITT, 1987; IMBENS and ANGRIST, 1994; HECKMAN et al., 1997; CARD, 2001; HECKMAN and VYTLACIL, 2005, 2007a, b). 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. If we let 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:

(1) $$y = dy_1 + (1-d)y_0 .$$

For any household, the causal effect of the adoption on its observed outcome y is simply the difference between 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. Such a population parameter is called the average treatment effect (ATE) in the literature (IMBENS and WOOLDRIDGE, 2009). One can also estimate the mean effect of adoption on the sub-population of adopters – $E(y_1 - y_0 | d = 1)$ – which is called the average treatment effect on the *treated* and is usually denoted by ATT. The average treatment effect on the *untreated* – $E(y1\text{-}y0 \mid d{=}0)$ – denoted by ATU is another population parameter that can be defined and estimated. Several methods have been proposed in the statistical and econometric literature to remove (or at least minimize) the effects of overt bias (caused by selection on observables) and hidden biases (caused by selection on unobservables), and deal with the problem of non-compliance or endogenous treatment variable. The methods can be classified under two broad categories based on the types of assumptions they require to arrive at consistent estimators of causal effects (see IMBENS, 2004; IMBENS and WOOLDRIDGE, 2009).

First, there are the methods designed to remove overt bias only. These are based on the 'ignorability' or conditional independence assumption (RUBIN, 1974; ROSENBAUM and RUBIN, 1983), which postulates the existence of a set of observed covariates $\boldsymbol{x}$, which, when controlled for, renders the treatment status d independent of the two potential outcomes y_1 and y_0 and has been widely used in the literature (IMBENS AND WOOLDRIDGE, 2009). 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 $P(d = 1| x) \equiv P(x)$ (called the *propensity score)*, is estimated in the first stage and ATE, ATT and ATU are estimated in the second stage by parametric regression-based methods or by non-parametric methods. The latter include various matching method estimators such as those used by GU and ROSENBAUM (1993), ROSENBAUM (1989, 1995, and 2002), RUBIN (1973b and 1979), DEHEJIA and WAHBA (1999), ABADIE et al. (2002), ABADIE and IMBENS (2006), MENDOLA (2007), DIAMOND and SEKHON (2008), SEKHON and GRIEVE (2008), ROSENBAUM and RUBIN (1985), and IACUS et al. (2008). In this study, the conditional independence-based estimators of ATE, ATT and ATU that were used are the so-called inverse propensity score weighing estimators (IPSW), which are given by the following formulae (IMBENS, 2004; LEE, 2005; HIRANO et al., 2000 and 2003):

(2) $$AT\hat{E} = \frac{1}{n}\sum_{i=1}^{n}\frac{(d_i - \hat{p}(x_i))y_i}{\hat{p}(x_i)(1-\hat{p}(x_i))}$$

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

(4) $$A\hat{T}U = \frac{1}{1-n_1}\sum_{i=1}^{n}\frac{(d_i - \hat{p}(x_i))y_i}{\hat{p}(x_i)}$$

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 $\hat{p}(x_i)$ is a consistent estimate of the propensity score evaluated at $\boldsymbol{x}$. We use a probit specification to estimate the propensity score.

Secondly, there are instrumental variable (IV)-based methods (HECKMAN and VYTLACIL, 1999, and 2005; HECKMAN and ROBB, 1985; MANSKI and PEPPER, 2000; 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 assume the existence of at least one variable, an instrument called $\boldsymbol{z}$, 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. Other recent papers on semi-parametric and non-parametric models with non-separable error terms and an endogenous, possibly continuous, covariate include papers using quantile instrumental variable methods, such as CHERNOZHUKOV and HANSEN (2005) and CHERNOZHUKOV et al., (2006), and papers using a control function technique, such as ALTONJI and MATZKIN (2005), BLUNDELL and POWELL (2004), CHESHER (2003 and 2007), and IMBENS and NEWEY (2002). In this study, we propose to use two instrumental variable (IV)-based estimators to estimate the Local Average Treatment Effect (LATE) of adoption of NERICA on productivity, income and poverty of Nigerian rice farmers (IMBENS and ANGRIST, 1994). The first one is the simple non-parametric Wald estimator proposed by IMBENS and ANGRIST (1994), which requires only the observed outcome variable y, the treatment status variable d, and an instrument z. The second IV-based 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 x, a vector of covariates that determines the observed outcome y.

Following the IMBENS and ANGRIST (1994) LATE estimator and that of ABIDIE (2003), we note that a farmer's exposure status to the NERICA varieties (i.e. his awareness of the existence of the NERICA varieties) is a 'natural' instrument for the NERICA adoption status variable (which is the treatment variable here). Firstly, one cannot adopt a NERICA variety without being aware of it and we do observe some farmers adopting NERICA (i.e. awareness does cause adoption). Secondly, it is natural to assume that exposure to NERICA affects the overall household income and poverty outcome indicators only through adoption (i.e. the mere awareness of the existence of a NERICA variety without adopting it does not affect the poverty outcome indicators of a farmer). Hence, the two requirements for the NERICA exposure status variable to be a valid instrument for the NERICA adoption status variable are met.[1] 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 status of the farmer with and without exposure to the NERICA varieties, respectively (with 1 indicating adoption and 0 otherwise).

Because one cannot adopt a NERICA variety 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 sub-population 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 poverty outcome of the sub-population of NERICA potential adopters (i.e. the LATE) is as given by

[1] The usual third requirement that the instrument be "uncorrelated with the unobserved error term" made in classical IV can be weakened by the ABADIE (2003) generalization of the LATE identification estimation through the Local Average Response Function (LARF).

$$E(y_1 - y_0 \mid d_1 = 1) = LATE = \frac{\text{cov}(y,z)}{\text{cov}(d,z)}$$

(5)
$$= \frac{E(y|z=1) - E(y|z=0)}{E(d|z=1) - E(d|z=0)}$$

$$= \frac{E[y_i \cdot (z - E[z_i])]}{E[d_i \cdot (z - E[z_i])]}$$

which is the well known *Wald* estimator that can be estimated using two-stage least squares. (IMBENS and ANGRIST, 1994; IMBENS and RUBIN, 1997 a and b; LEE, 2005). For applications using parametric models with covariate, see HIRANO et al. (2000) and MEALLI et al. (2004). Moreover, it has been shown that, under the same assumptions, the entire marginal distributions of potential outcomes are identified for compliers (IMBENS and RUBIN, 1997a and b, and ABADIE, 2003). In particular, ABADIE (2003) shows that if those assumptions[2] hold in the absence of covariates:

$$E(y_1 \mid d_1 > d_0) = \frac{E(y \cdot d|z=1) - E(y \cdot d|z=0)}{E(d|z=1) - E(d|z=0)}$$

$$E(y_0 \mid d_1 > d_0) = \frac{E(y \cdot (1-d)|z=1) - E(y \cdot (1-d)|z=0)}{E((1-d)|z=1) - E((1-d)|z=0)}$$

These equations identify average treatment responses for compliers.

The assumption that exposure to the NERICA varieties is random in the population is, however, unrealistic given the way the dissemination of NERICA took place in Nigeria (PVS). We therefore use ABADIE's (2003) LATE estimator, which does not require the randomness assumption but instead requires the 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. With these assumptions, the following results can be shown to hold for the conditional mean outcome 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) (ABADIE, 2003; LEE 2005):

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

(7) $$E(g(y,d,x)|d_1 = 1) = \frac{1}{P(d_1 = 1)} E(k \cdot g(y,d,x))$$

[2] (i) Independence of the instrument: Conditional on X, the random vector (Y00; Y01; Y10; Y11; D0; D1) is independent of Z. (ii) Exclusion of the Instrument: $P(Y1d{=}Y0d|x){=}1$ *for* $d \in \{0,1\}$. (iii) First Stage: $0<P(Z=1|x)<1$ *and* $P(d1{=}1|x)>P(d0{=}1|X)$. (iv) Monotonicity : $P(d1 \geq d0|x){=}1$

Where $k = 1 - \frac{z}{p(z=1|x)}(1-d)$ 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 Response Function (LARF) by ABADIE (2003). Estimation proceeds by a parameterization of the LARF $f(\theta; x, d) = E(y|x, d; d_1 = 1)$. Then, using equation (3) 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 (7) is used to recover the conditional mean treatment effect $E(y_1 - y_0|x, d_1 = 1)$ 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 $E(y_1 - y_0|x, d_1 = 1) = \alpha$. 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 local average response function with no interaction between d and x implies a constant treatment effect across the sub-population of potential adopters. In this study, we postulate an exponential conditional mean response function with and without interaction to guaranty both the positivity of predicted outcomes (poverty productivity) and heterogeneity of the treatment effect across the sub-population of potential NERICA adopters. Because exposure (i.e. awareness) is a necessary condition for adoption, it can be shown that the LATE for the sub-population of potential adopters (i.e. those with d_1=1) is the same as the LATE for the sub-population of *actual* adopters (i.e. those with $d=zd_1$=1).

2.2.2 The Poverty Decomposition Model

The FOSTER, GREER and THORBERKE (1984) poverty model (FGT) was used to decompose farmers into various poverty statuses. The procedure entails estimating the different poverty indices using the farm-household data set; the number of rice farming households in the region that were below a poverty line was therefore calculated. The depth and severity of poverty was also calculated using poverty indices. Income changes resulting from adoption of the new varieties and changes in the number of households and depth of poverty were also estimated. The poverty measure itself is a statistical function that translates the comparison of the indicator of household well-being and the chosen poverty line into one aggregate number for the population as a whole or for a population sub-group (FOSTER et al., 1984). The FGT index used is given by:

(8) $$P_\alpha = \frac{1}{n}\sum_{i=1}^{q}\left(\frac{Z - Y_i}{Z}\right)^\alpha$$

where $\alpha \geq 0$ and takes the values of 0, 1 and 2 for, respectively, poverty incidence, depth and severity; q = the number of people with an income below the poverty line, Yi = income of the ith household, n = total population and Z = poverty line.

When $\alpha = 0$, P_0 gives the Incidence of Poverty (Headcount Index,); $\alpha = 1$, P_1 gives the Depth of Poverty (Poverty Gap,) and $\alpha = 2$, P_2 gives the Poverty Severity (Squared Poverty Gap).

3 Data and Descriptive Statistics

This study was based on survey data collected in 2008/2009 from three agro-ecological zones of Nigeria where NERICA dissemination activities were being conducted. A multistage sampling technique was used for the collection of the data. We stratified the sampling frame into three strata according to the main rice farming systems practiced in Nigeria: (i) upland; (ii) lowland; and (iii) irrigated rice. From each stratum, one state was randomly selected. The second stage involved listing the Local Government Areas and villages that practice rice farming in each state selected. We, therefore, selected 15 villages from Kano, 16 villages from Osun and 17 villages from Niger State. We selected both villages where NERICA varieties had been introduced and those where they were not yet introduced. A total of 48 villages were selected and rice farmers were randomly selected in each village to generate a total of 481 respondents after data cleaning.

Evidence from table 1 reveals that the majority of respondents (93.1%) and 90% of the adopters of NERICA varieties were male. At the time of the survey, the average age of the farmers was 47 years. The average household size of respondents (both adopters and non-adopters) was 10 people per family; about 83.3% of respondents were native to their respective villages and had spent an average of about 42 years in their villages. The educational level of the household's head was significantly different between adopters and non-adopters. Whereas 14.5% of the adopters had at least primary school level of education, 34% of non-adopters had a similar level of education. In addition, there was a significant difference in the attendance of vocational training as well as in the type of experience in rice farming between adopters and non-adopters of NERICA varieties. It appears that about 21% of NERICA non-adopters and adopters, respectively, reported having contact with National Cereal Research Institute (NCRI) or Agricultural Development Programs (ADPs).

4 Results and Discussion

4.1 Impact on Income and Poverty using Mean Difference

Table 2 presents the mean difference analysis of the impact of NERICA adoption in terms of area cultivated, rice output, yield, household expenditure, annual per capita expenditure, annual income and poverty status between adopters and non-adopters of NERICA varieties. As for the welfare impact of NERICA, a straightforward comparison between both household income and per capita expenditure of adopters and non-adopters was considered. While household income indicates the ability of the household to purchase its basic needs of life, per capita expenditure reflects the effective consumption of households and therefore provides information on the food security status of households. The result shows that while there is a significant difference between the gross incomes of adopters and non-adopters, there was no significant difference in the amount spent per head by both groups. As is evident from the table, the incidence of poverty was higher among non-NERICA adopters (50.2%) than NERICA adopters (45.5%). In addition, both the depth and severity of poverty were also higher (19.25% and 10.02%) among non-adopters than the adopters (15.28% and 7.76%). All three poverty measures indicate that poverty was more prevalent and severe among non-adopters compared to adopters. These results are consistent with recent studies in this area (MENDOLA, 2007; DIAGNE et al., 2009; JAVIER and AWUDU, 2010).

The mean differences in per capita expenditure, poverty rate, and other household characteristics of adopters and non-adopters indicate that adopters of NERICAs are better off than the non-adopters. However, the differences in observed mean outcomes between adopters and non-adopters cannot be attributed entirely to NERICA adoption due to the problem of self-selection and non-compliance (HECKMAN and VYTLACIL, 2005; IMBENS and ANGRIST, 1994). The impact of the adoption of new technologies (NERICA varieties) on per capita expenditure, poverty and income levels is discussed in the next section.

4.2 The Impact on Poverty and its Determinants

The empirical impact results are given in tables 3 to 6. Table 3 shows that the adoption of improved rice varieties exerts a positive and significant impact on the per capita expenditure in Nigeria. Specifically, LATE estimates suggest that NERICA adoption significantly increased the household per capita expenditure by about ₦4739.96. This is the average change in per capita expenditure of households that belongs to a change in technological status. The results further reveal that the impact was much higher among male farmers than their female counterparts. Comparison ecologies also shows that the highest impact of NERICA adoption was observed in the irrigated ecology where per capita expenditure increased by ₦2516.23, followed by the rainfed lowland and rainfed upland with respective increases of ₦1907.06 and ₦1373.83. These results suggest that the causal effect of NERICA adoption on poverty reduction was greater for farmers previously recorded as falling within the depth of poverty experienced by those in poverty headcount and poverty severity, respectively.

In terms of causal effects, the estimates of the LATE appear to be similar to those of the ATE-IPSW. However, the LATE estimates are quite different from the ATE estimates. As indicated earlier, the ATE estimates of the impact of NERICA adoption on outcomes of interest do not have a causal interpretation due to the problem of non-compliance.

The determinants of household per capita expenditure as given by their local average response functions (LARF) are presented in table 4. These estimates provide evidence that, apart from a change in technology (NERICA adoption), other household socio-demographic variables significantly explain the change in per capita expenditure. These variables include gender, age of the household head, household size, farm size and years of experience in upland rice farming. Similarly, a number of coefficients for the interacted terms were statistically significant, thus confirming the heterogeneity of the impact of NERICA adoption on expenditure. The F statistics of 2023.74 for the joint significance of the interacted terms as well as the non-interacted terms indicate that they are jointly statistically significantly different from zero. Whereas the coefficient (13.75) for gender of the household head is positively significant, indicating male-headed households have higher per capita expenditure than female-headed households, the coefficient (-0.13 and -0.08) for household size and age were negatively significant, suggesting that larger households and elderly people spend less per person than smaller households. Farm size and the number of years spent in upland rice were also significant at the 1% level, showing that increases in any of these variables would lead to an increase in PCE. Furthermore, the negative significance of the interaction term for gender and household size suggests that the impact of NERICA adoption on per capita household expenditure is going to be smaller among female farmers and larger households while the positive significance of the interaction terms of age and farm size suggests that the impact of NERICA adoption will be high for elderly farmers and those with large farm sizes.

4.3 The Impact on Household Income and its Determinants

The impact of improved technology adoption on household income of rice farmers was estimated through the local average treatment effect (LATE). Results presented in table 5 show that NERICA adoption had a positive and significant effect on household income. Adoption of NERICA increased the income of adopters by ₦63771.94. Using ABADIE's LATE estimator, the figure of ₦63771.94 (column 1) is significantly larger in magnitude than the Wald estimate of ₦39109.2 (column 2). Similar results were observed in previous studies which show a positive impact of the adoption of agricultural technologies (WINTERS et al., 1998; MWABU et al., 2006; DE JANVRY and SADOULET, 2002; MENDOLA, 2007, and DIAGNE et al., 2009). The impact is significantly higher in households headed by males (₦66882.43) than in those headed by females (₦28519.68). Moreover, analysis across ecologies indicates that the impact was greatest in rainfed upland (₦49858.770), followed by rainfed lowland (₦41288.69) and the irrigated ecology (₦153747.7). This may be due to the fact that the upland rice system is the most widely practiced and also because the first NERICA variety officially released in Nigeria was an upland type. In addition, adoption of NERICA significantly increased the income of farmers within the poverty severity grouping more than that of farmers classed within the poverty headcount and poverty gap, showing that NERICA can be used as a poverty-reducing crop among rural farmers. This finding is in line with that of KIJIMA et al. (2008) who found that adoption of the New Rice for Africa (NERICA) varieties in Uganda had the potential to reduce poverty significantly without deteriorating the income distribution.

The LATE estimates are quite different from the ATE estimates. However, as indicated earlier, the ATE estimates of the impact of NERICA adoption on our outcomes of interest do not have a causal interpretation due to the problem of non-compliance. The ATE estimate based on the propensity score matching method (column 3), is smaller in magnitude (₦ 63771.94) compared to the LATE based on IV estimate in column 1.

The determinants of household income as given by their local average response functions (LARF) were estimated and the results in table 6 indicate that, apart from a change in technology used (NERICA adoption), other household socio-demographic variables significantly explain the change in household income. These variables include gender and age of the household head, education level and household size. A number of coefficients for the interacted terms were also statistically significant, thus confirming the heterogeneity of the impact of NERICA adoption on household income. Furthermore, F-statistics of 1835.35 for the joint significance of the interacted terms as well as the non-interacted terms indicate that they are jointly statistically significantly different from zero. The coefficient (0.72) for the gender of the head of household is positive and significant, indicating that male-headed households have higher income than female-headed households. The coefficients (0.33 and 0.08) of the household size and age are positive and significant at 1% level, showing that increases in any of these variables would lead to an increase in household income. This suggests that larger households and elderly people generate more income than smaller households and younger farmers. This may be explained by the fact that rice production is highly labor–demanding, and that labor cost covers the higher percentage of the total production cost. Large household size is therefore a source of family labor, which may reduce the labor cost and thereafter increase the total revenue from production. Furthermore, older farmers are the more experienced in terms of resource allocation.

The interaction term for gender and household size is negative and significant, suggesting that the impact of NERICA adoption on per capita household expenditure will be smaller among female farmers and larger households. However, the interaction terms of age and farm size are positive and significant, suggesting that the impact of NERICA adoption will be high for elderly farmers and those with large farm sizes.

5 Conclusions and Recommendations

This study examined the impact of the adoption of different NERICA varieties on household income and poverty status proxy by per capita expenditure in three states of Nigeria. Given the non-experimental nature of the data used in the analysis, associated with the biases and non-compliance behavior of some farmers, a local average treatment effect model was used. Also, the local average response function was used to account for other factors that could have affected our outcomes. The results did suggest the presence of bias in the distribution of covariates between groups of adopters and non-adopters, indicating that accounting for selection bias is a significant issue.

Overall, the findings in this study indicate that adoption of improved varieties helped raise farmers' income and per capita expenditure, thereby increasing their probability of escaping poverty. This confirms the widely held view that productivity-enhancing agricultural innovations can contribute to raising incomes of farm households, poverty alleviation and food security in developing countries. However, it is noteworthy to mention that the results from this study, as well as observations from other studies, such as BELLON and RISOPOULOS (2001), DIAGNE et al. (2009) and JAVIER and AWUDU (2010), show that farmers in these states generally continue to use the traditional rice varieties alongside the improved ones. This suggests that intervention programs to help extend the high yielding rice varieties to areas with high poverty rates is therefore a reasonable policy instrument to raise incomes in these areas, although complementary measures are needed. As noted by MORRIS et al. (1999), improved technology is certainly a requirement for changing farming practices, but elements such as effective extension services, improved access to land, an efficient input distribution system and appropriate economic incentives must also be present.

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Appendices

Table 1. Household socio-economic characteristics by adoption status

Characteristic	Non-Adopters (n=380)	Adopters (n=101)	Total (n=481)	Difference Test
Socio-demographic factors				
Proportion of male farmers (%)	93.8	90.0	93.1	0.04
Proportion of female farmers (%)	6.2	10.0	6.9	0.04
Age (average)	45	49	47	3.4***
Household size (average)	10	10	10	0.0
% born in the village	63.6	16.42	80.04	0.02
Number of years of residence in the village (average)	42	43	42	1.0
Education and experience in rice farming				
% of no formal education	45.9	6.9	52.8	0.25***
% of primary school	17.3	7.4	24.7	0.14***
% of secondary school	13.1	6.4	19.53	0.14***
% of post secondary school	3.7	0.2	2.9	0.02
Proportion of farmers that receive vocational training (%)	5.8	5.8	11.6	0.20***
Proportion of farmers with experience in lowland rice farming (%)	53.6	0.62	54.2	0.65***
Proportion of farmers with experience in upland land rice farming (%)	10.8	17.9	28.7	0.71***
Proportion of farmers with experience in mangrove rice farming (%)	15.0	1.5	16.4	0.12***
Institutional factors				
Proportion of farmers in contact with NCRI	11.0	1.7	12.68	0.06*
Proportion of farmers in contact with ADPs	8.3	0.2	8.5	0.10***

NB: The T-test was used to test for difference in socio-economic/demographic characteristics between adopters and non-adopters.

Legend: * significant at 10%; ** significant at 5% and *** significant at 1%

Source: AfricaRice/NCRI Base line and priority setting survey 2009, NERICA impact study

Table 2. Descriptive analysis of the impact of NERICA adoption

Characteristic	Non-Adopters (n=380)	Adopters (n=101)	Total (n=481)	Difference Test
Area cultivated	3.68 (0.18)	2.82 (0.84)	3.50 (0.23)	0.85** (0.57)
Yield	2075.72 (160.53)	2577.57 (180.62)	2181.10 (132.62)	-501.85** (325.14)
Rice output	2028.41 (134.08)	1360.01 (92.62)	1887.76 (108.32)	668.39** (264.27)
Annual household expenditure	72549.99 (4339.03)	72797.8 (4464.46)	72603.17 (3538.03)	-247.81 (8627.03)
Male farmers	70543.18 (4462.90)	72971.69 (4750.75)	71045.83 (3671.34)	-2428.50 (9071.74)
Female farmers	99922.8 (17596.31)	71390.91 (13661.89)	91204.72 (12987.41)	28531.89 (28184.14)
Annual household per capita expenditure	9588.92 (786.32)	9877.71 (1016.98)	9650.89 (654.57)	-288.78 (1596.09)
Male farmers	9195.31 (814.57)	9670.07 (1105.67)	9293.58 (684.85)	-474.76 (1692.23)
Female farmers	14957.8 (2856.68)	11557.64 (2392.45)	13918.86 (2110.88)	3400.15 (4612.66)
Annual income of the household	153129.6 (8267.34)	84379.29 (8455.41)	138693.5 (6884.49)	68750.32*** (16626.52)
Male farmers	155590.2 (8580.42)	90840.46 (9160.71)	64749.75 (7187.26)	64749.75*** (17599.78)
Female farmers	122196.4 (30824.97)	31515.15 (11832.62)	96619.66 (23214.63)	90681.28* (50110.2)
Poverty measure				
Headcount ratio (incidence)	50.2 (3.9)	45.54 (5.8)	49.27 (3.78)	
Poverty gap (depth)	19.25 (2.18)	15.28 (2.70)	18.42 (2.01)	
Poverty severity	10.02 (1.90)	7.76 (2.05)	9.54 (1.76)	

Source: AfricaRice/NCRI Base line and priority setting survey 2009, NERICA impact study

Table 3. The impact of NERICA adoption on per capita expenditure

Parameters	LATE	LATE –Wald	ATE-ps	ATE-ipsw	ATE-exp
ATE	4739.96	1390.26***	3179.35	4739.96	2223.69
ATE1			-979.49	4861.57***	1548.35*
ATE0			4315.65	4706.73	2408.21
PSB			-4158.84	121.61	-675.33
Impact by gender					
Male	1635.71*** (0.00)				
Female	-1541.52** (0.00)				
Impact by state					
Osun	-1373.83*** (0.00)				
Niger	1907.06*** (0.00)				
Kano	2516.23*** (0.00)				
Impact by poverty status					
Headcount ratio (incidence)	1462.93*** (0.00)				
Poverty gap (depth)	1568.65*** (0.00)				
Poverty severity	662.19*** (0.00)				

Source: AfricaRice/NCRI Base line and priority setting survey 2009, NERICA impact study

Table 4. Estimated coefficient of the exponential local average response function (LARF) for per capital expenditure

Per Capita Expenditure	Coef.	Std. Err.	t-statistics
NERICA adoption	11.00	0.80	13.82***
Age	-0.08	0.01	-8.37***
Sex	13.75	0.36	38.22***
No formal education dummy	-0.05	0.18	-0.25
Primary education dummy	0.01	0.19	0.07
Secondary education dummy	-0.15	0.34	-0.45
Household size	-0.13	0.03	-4.67***
Number of years in upland rice	0.05	0.02	2.62***
Farm size	0.23	0.04	6.28***
Age_adoption	0.08	0.02	4.00***
Sex_adoption	-13.39	0.56	-23.85***
Osundum_adoption	-0.55	0.53	-1.04
Nigerdum_adoption	-0.20	0.41	-0.49
ADPdum_adoption	0.05	0.91	0.06
NCRIdum_adoption	1.07	2.73	0.39
Household size_adoption	-0.11	0.06	-1.73*
Number of years in upland rice_adoption	0.04	0.03	1.23
Farm size_adoption	0.19	0.11	1.75*
R-squared	0.49		
Adj R-squared	0.47		
Wald test for the joint significance of all coefficients	2023.74***		
Wald test for non-interacted terms	130.23***		

Source: AfricaRice/NCRI Baseline and priority setting survey 2009, NERICA impact study

Table 5. The impact of NERICA adoption on household rice income

Parameters	LATE	LATE-Wald	ATE-ps	ATE-ipsw	ATE-exp
ATE	63771.94*** (11257.71)	39109.2***	63771.94**	-21176.91	-29765.75
ATE1			41006.46**	-21509.15	-21017.2
ATE0			69822.76**	-21088.6	-32091.02
PSB			-22765.48	-332.24	8748.553*
Impact by gender					
Male	66882.43*** (13115.41)				
Female	28519.68*** (20551.35)				
Impact by state					
Osun	49858.77*** (9535.52)				
Niger	41288.69*** (10023.84)				
Kano	153747.7*** (54083.31)				
Impact by poverty status					
Headcount ratio (incidence)	69171.67**** (10858.55)				
Poverty gap (depth)	52718.12*** (10073.53)				
Poverty severity	72752.3*** (32014.09)				

Source: AfricaRice/NCRI Base line and priority setting survey 2009, NERICA impact study

Table 6. Estimated coefficient of the exponential local average response function (LARF) for household income

Rice income	Coef.	Std. Err.	t-statistics
NERICA adoption	11.50	1.67	6.90***
Age	0.08	0.01	6.12***
Sex	0.72	0.29	2.46**
No formal education dummy	-3.18	0.76	-4.17***
Primary education dummy	2.85	0.29	9.97***
Secondary education dummy	3.48	0.47	7.44***
Household size	0.33	0.03	10.62***
Number of years in upland rice	-0.10	0.08	-1.30
Farm size	0.03	0.04	0.73
Age_adoption	-0.08	0.03	-2.76***
Sex_adoption	0.55	1.46	0.37
Osundum_adoption	-0.86	0.74	-1.16
Nigerdum_adoption	-1.59	0.87	-1.83*
ADPdum_adoption	0.05	0.72	0.06
NCRIdum_adoption	-0.34	2.94	-0.12
Household size_adoption	-0.34	0.06	-5.16***
Number of years in upland rice_adoption	0.11	0.09	1.25
NERICA adoption	-0.03	0.14	-0.22
R-squared	0.30		
Adj R-squared	0.27		
Wald test for the joint significance of all coefficients	1835.35***		
Wald test for non-interacted terms	159.07***		

Source: AfricaRice/NCRI Baseline and priority setting survey 2009, NERICA impact study