Impact of Improved Agricultural Technology Adoption on Sustainable Rice Productivity and Rural Farmers' Welfare in Nigeria: A Local Average Treatment Effect (LATE) Technique

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Abstract

This study examined the impact of improved rice varieties adoption on rice productivity and farming households' welfare in Nigeria using a cross sectional data of 481 rice farmers drawn from three states to represent the major rice producing ecologies (Irrigated, upland and lowland) in Nigeria. Access to seed was found to be one of the significant determinants of adoption. Poverty incidence was also higher among the non-adopters than the adopters. This study also adopted the counterfactual outcomes framework of modern evaluation theory to provide a consistent estimate of the impact. Specifically, the LATE which uses the system of instrumental variable method was adopted to assess the impact of improved rice varieties adoption on rice productivity and total household expenditure (Proxy for welfare). The results showed a significant positive impact of on rice productivity (358.89kg/ha) and total households' expenditure (₦32890.82) This suggests that adoption of improved rice varieties significantly generate an improvement in farming household living standard. Hence, efforts should be intensified to ensure farmers have access to adequate quality improved rice seed at the right time. All programs, strategies and policies that could lead to increase in improved rice adoption should be intensified in order to achieve the much desired poverty reduction and generate an improvement in rural farming households' welfare in Nigeria.

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1.0. INTRODUCTION

One of the overarching goals of Nigerian agriculture development programs and policies is increasing agricultural productivity for accelerated economic growth. Particularly, majority of the poor in Sub-Saharan Africa depend on agriculture for survival thus, agricultural sector has been recognized as a key fundamental for spurring growth, overcoming poverty, and enhancing food security. Productivity increases in agriculture can reduce poverty by increasing farmers' income, reducing food prices and thereby enhancing increments in consumption (Diagne et al., 2009). Consistent with this argument, the Department for International Development (2003) estimated that a 1% increase in agricultural productivity reduces the percentage of poor people living on less than 1 dollar a day by between 0.6 and 2%, and no any other economic activity generates the same benefit for the poor. It is also of considerable significance that when agricultural production increases through the use of improved varieties of crops in a given area, farmers and their communities derive added socio-economic benefit. Such activities can increase the value of locally produced crops, generate local employment, stimulate local cash flow, and through processing, marketing, and related activities can bring about improvement in socio-economic status and the quality of life (Nwabu et al, 2006).

However, several research findings have pointed to the fact that the use of new agricultural technology, such as high yielding varieties that kick-started the Green Revolution in Asia, could lead to significant increase in agricultural productivity in Africa and stimulate the transition from low productivity subsistence agriculture to a high productivity agro-industrial economy (World Bank, 2008). This implies that agricultural productivity growth will not be possible without developing and disseminating cost effective yield-increasing technologies, since it is no longer possible to meet the needs of increasing numbers of people by expanding the area under cultivation or relying on irrigation (Datt and Ravallion, 1996; Hossain, 1989).

Against this background, government has at various points in time adopted policies programs and strategies in order to achieve a sustainable increase in agricultural productivity. In particular efforts have been focused on increase in rice production. This is because rice has become a national commodity because of its importance in the Nigerian diets; majority of the population live on rice and their primary food security is entirely dependent on the volume of rice produced. Also in the producing areas for instance, it provides employment for more than 80% of the inhabitants as a result of the activities that take place along the distribution chains from cultivation to consumption (Ogundele and Okoruwa, 2006). Among all the several efforts geared towards increase in rice productivity, the development and dissemination of improved rice varieties appear to the most remarkable. This is due to the fact that seed is the key input in agriculture and to a great extent the yield and quality of the crop depend on the quality of the seed planted. Furthermore, the attributes of the seed planted in terms of its genetic potential, purity and germination, resistance to disease, its adaptation to local agro-ecological situation among many others, set a limit to the gains in productivity to be attained from the use of expensive inputs like fertilizer, pesticide, herbicide and management techniques (Adekoya and Babaleye, 2009). Additionally, the improved rice varieties enables farmers to crop several times within a planting period because of a relatively short growing period, the genetic potential of these seeds also ensures bumper harvests, disease and pest resistance, and drought tolerance; the improved varieties can compete favorably with weeds (AfricaRice, 2008). Therefore, with the help of international donors several improved rice varieties have been developed such that in Nigeria for example, at least 57 improved rice varieties have been developed and disseminated to the farmers through different programs and projects.

However, despite all these efforts, several research findings revealed that rural farmers in most cases find it difficult to obtain good quality seeds that are suitable to their local conditions. Also, recurrent droughts in some areas particularly in the northern part of Nigeria have resulted into local seed stocks being exhausted due to the conversion of seeds into food and the stocks are not being replenished year in year out due to crop failure. In addition, commercial producers of improved seed of good quality are not available in most rural areas and local business people are reluctant to stock seed due to uncertainty in demand. This could have negative effect of adoption in view of the fact that if a farmer does not have access to improved varieties, adoption would be impossible and there would be no yield increase. For instance, despite the release of nearly 1700 improved wheat varieties in developing countries during the period 1988-2002, only a relatively small number has been adopted on a substantial scale by farmers (Dixon et.al, 2006). Christensen and Cook (2003) also discovered that despite a good history of development of varieties of millet, sorghum, maize, rice and cowpea, most Malian farmers still retained their own seed or exchanged with nearby farmers; few used improved high yielding varieties . Longley and Sperling (2002) discovered that studies of seed security in most disaster situations increasingly indicated that good quality seed was locally available in many emergencies and that often the problem was that some farmers lacked access to quality seed.

Furthermore, as noted by Seck (2008) one of the biggest constraints to the successive adoption of improved varieties is the availability of seed. Meanwhile, access to seed is a necessary condition for improved seed adoption (Dontsop-Nguezet et al, 2011) and the adoption of improved seed is an important component of agricultural productivity, food security and sustainable economic growth (Faltermeier and Abdulai, 2009). Therefore, the persistence of lack of access to certified improved rice seed can jeopardise the efforts to achieve self-sufficiency in rice production, and the dependence on import would continue to expose the nation to international shocks such as the 2008 global food crisis which led to a global doubling of prices of major staple food crops such as rice, maize and wheat. Therefore this study was conducted to assess the determinants of adoption of improved rice varieties in Nigeria and also provide a consistent estimate of the impact of adoption on rice productivity and welfare of the farming households using LATE estimation techniques to deal with the problem of non-compliance. This is because the impact on the lives of resource poor farmers is believed to be the most functional benefit of agricultural technologies, policies and programmes and also the preoccupation of the stakeholders (Collinson and Tollens, 1994). However, the mixed results of development assistance has generated a lot of questions of whether and by how much development assistance contributes to economic growth and poverty reduction in recipient (Rajan and Subramanian 2005, Easterly 2001). Increasingly, therefore the development community, including donors and governments are looking for more hard evidence on impacts of public programs aimed to reduce poverty. Hence, poverty impact assessment has received a considerable attention in recent years.

2.0. Literature Review

The problem of evaluating the effect of a binary treatment or programme is a well studied problem with a long history in both econometrics and statistics. The econometric literature goes back to early work by Ashenfelter (1978) and subsequent work by Ashenfelter and Card (1985), Heckman and Robb (1985), Lalonde (1986), Fraker and Maynard (1987), Card and Sullivan (1988), and Manski (1990). The focus in the econometric literature is traditionally on endogeneity or self-selection issues and motivated primarily by applications to the evaluation of labour market programmes in observational settings. Individuals who choose to enrol in a training programme are by definition different from those who choose not to enrol. These differences, if they influence the response, may invalidate causal comparisons of outcomes by treatment status, possibly even after adjusting for observed covariates (Imbens and Woodridge, 2008).

Consequently, different methods have been developed and used in the literature to assess the impact of programs, policies and adoption of improved agricultural technologies on poverty reduction or welfare however, the results have been mixed. For instance Mendola adopted the Propensity Score Matching (PSM) methods to assess the impact of agricultural technology adoption on poverty in Bangladesh and observes that the adoption of high yielding improved varieties has a positive effect on household wellbeing in Bangladesh. In the same vein, Kijima et.al. (2008) conducted a study on the impact of New Rice for Africa (NERICA) in Uganda and found that NERICA adoption reduces poverty without deteriorating the income distribution. Diagne (2006) also assess the impact of NERICA adoption on rice yield in Cote d'Ivoire. The results show a positive and significant increase in yield particularly on the female farmers. Other studies that also show a positive impact of NERICA adoption include; Winter et.al.,(1998) ; De Janvry and Sadoulet (1992) and Dontsop-Nguezet et.al, (2011). In contrast however, a study conducted by Hossain et.al.(2003) in Bangladesh reveals that the adoption of improved varieties of rice has a positive impact on the richer households but had a negative effect on the poor. Furthermore, in another study conducted by Bourdillon et al. (2002) reveals that the adoption of improved varieties of maize leads to a moderate increase in income of the adopters.

More recently, Dontsop-Nguezet et.al.(20110 also examine the impact of NERICA adoption on farmers welfare in Nigeria. The result of the study shows that adoption of NERICA varieties has a positive and significant impact on farm household income and welfare measured by the per capita expenditure and poverty reduction in rural Nigeria. However, a close examination of the all above studies showed that majority of the studies focused on NIERICA; however, NERICA is just one of the numerous improved rice varieties that have been developed and disseminated to farmers. Particularly in Nigeria, at least 57 improved rice varieties have been released. Therefore, any observed impact of NERICA adoption cannot be generalised to the entire improved rice varieties adoption . More so NERICA was only disseminated in some selected states, which means that not all farmers were aware of the existence of NERICA and in addition only the upland NERICA varieties have been released so far and this could also further limits its adoption only to the upland rice farmers. Therefore this study was focused on all the existing improved rice varieties in Nigeria.

3.0. Analytical Framework and Estimation Technique

3.1. Determinants and intensity of Improved Agricultural Technology Adoption

In this study, a farmer was defined as an adopter if he or she was found to be growing any improved rice variety. Thus, a farmer could be classified as an adopter and still grow some traditional varieties. The adoption variable was therefore defined as 1 if a farmer is an adopter of improved rice variety and 0 otherwise. Although this issue of whether or not to treat adoption as a dichotomous choice was raised by Feder et al. (1985), but it continues to bedevil adoption studies, often because the available data limit analyses in this direction. This study adopted the logistic regression to assess the factors that determines the farmers' adoption status. The response variable was binary, taking values of one if the farmer adopts and zero otherwise. However, the independent variables were both continuous and discrete. The justification for using logit is its simplicity of calculation and that its probability lies between 0 and 1. Moreover, its probability approaches zero at a slower rate as the value of explanatory variable gets smaller and smaller, and the probability approaches 1 at a slower and slower rate as the value of the explanatory variable gets larger and larger (Gujarati, 1995).

Hosmer and Lemeshew (1989) pointed out that the logistic distribution (logit) has got advantage over the others in the analysis of dichotomous outcome variable in that it is extremely flexible and easily used model from mathematical point of view and results in a meaningful interpretation. The parameter estimates of the model were asymptotically consistent and efficient. The standardised coefficients correspond to the beta-coefficients in the ordinary least squares regression models. The binary logistic model does not make the assumption of linearity between dependent and independent variables and does not assume homoskedasticity (CIMMYT, 1993). Another advantage of using the logit model is that it does not require normally distributed variables and above all, the logit model is relatively easy to compute and interpret. Hence, the logistic model is selected for this study. The probability that a farmer will adopt at least one improved rice variety was postulated as a function of some socioeconomic, demographic characteristic and institutional factors. Therefore, the cumulative logistic probability model is econometrically specified as follows:

$$P_i = F(Z_i) = F(\gamma + \sum \lambda_i X_i) = \frac{1}{1+e^{-Z_i}} \quad (1)$$

Where P_i is the probability that a farmers will adopt at least one improved rice variety or not given Xi; e denotes the base of natural logarithms, which is approximately equal to 2.718; X_i represents the ith explanatory variables; and γ and λ are parameters to be estimated.

Hosmer and Lemeshew (1989) pointed out that the logit model could be written in terms of the odds and log of odds, which enables one to understand the interpretation of the coefficients. The odds ratio implies the ratio of the probability (P_i) that a farmer adopt to the probability ($1-P_i$) that the farmer is non-adopter.

$$(1-P_i) = \frac{1}{1+e^{Z_i}} \qquad (2)$$

Therefore

$$\frac{P_i}{1-P_i} = \frac{1+e^{z_i}}{1+e^{-z_i}} = e^{z_i} \qquad (3)$$

The natural log of equation (3), will give:

$$Z_i = \ln\left(\frac{P_i}{1-P}\right) = \gamma + \lambda_1 X_1 + \lambda_2 X_2 + \dots\dots + \lambda_m X_m \qquad (4)$$

If the disturbance term (U_i) is taken into account, the logit model becomes:

$$Z_i = \gamma + \sum_{i=1}^{m} \lambda_i X_i + U_i \qquad (5)$$

Equation (3) was estimated by maximum likelihood method. This procedure does not require assumptions of normality or homoskedasticity of errors in predictor variables. This analysis was carried using STATA version11.0.

Table 1: Description of variables used in the Logit model

Variable	**Definition**
Age	Age of household head in years
Gender	Gender of household head,1 male and 0 otherwise
Household size	Number of persons per households
Educational Background	Number of years of formal education of household head
Contact with extension agents	1 if farmer has contact with extension agent and 0 otherwise
Main occupation	1 if main occupation is farming and 0 otherwise
Log of income from other crops	Income from other crop production in Naira
Ownership of farm land	1 if farmer owns land and 0 otherwise
Access to mobile phone	1 if farmer owns a mobile phone, 0 otherwise

Years of experience rice production	Number of years of experience in rice production
Access to radio	1 if farmer owns a radio, 0 otherwise
Vocational training	1 if farmer attends vocational training, 0 otherwise
Distance to seed source	Distance to the nearest seed source(Km)
Access to seed	1 if a farmer have access to seed, 0 otherwise
Livestock	1 if farmer owns livestock, 0 otherwise

3.2. Econometric Framework for Impact Assessment

3.2.1 Inverse Propensity Score Weighting (IPSW) Techniques

Under the potential outcome framework developed by Rubin (1974), each farming household has *ex-ante* two potential outcomes: an outcome when adopting improved rice variety that we denote by y_1 and an outcome when not adopting improved variety that we denote by y_0. If we let the binary outcome variable *d* stand for improve variety adoption status, with *d* =1 meaning adoption and *d* =0 non-adoption, we can write the *observed* outcome *y* of any farming 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 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 farming households: $E(y_1 - y_0)$, where *E* is the mathematical expectation operator. Such a population parameter is referred to as the average treatment effect (ATE) in the literature. It is also possible to 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 ATE1 (or ATT). The average treatment effect on the *untreated*: *E*(*y1-y0* | *d*=0) denoted by ATE0 is also another population parameter that can be defined and estimated.

Several methods have been proposed in the statistics and econometric literature to remove (or at least minimize) the effects of overt and hidden biases 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). 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 ***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 $P(d = 1|\ x) \equiv P(x)$ (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; the latter include various matching method estimators such as those used by Mendola (2006). In this paper, the conditional independence-based estimators of ATE, ATE1 and ATE0 that we used are the so-called inverse propensity score weighing estimators (IPSW), which are given by the following formulae (see Imbens, 2004; Lee 2005, Diagne, 2006; Diagne et.al., 2009; Dontsop-Nguezet et.al. 2011 and Awotide et.al., 2011):

$$AT\hat{E} = \frac{1}{n}\sum_{i=1}^{n}\frac{\left(d_i - \hat{p}(x_i)\right)y_i}{\hat{p}(x_i)\left(1-\hat{p}(x_i)\right)} \quad (6)$$

$$AT\hat{E}1 = \frac{1}{n_1}\sum_{i=1}^{n}\frac{\left(d_i - \hat{p}(x_i)\right)y_i}{\left(1-\hat{p}(x_i)\right)} \quad (7)$$

$$AT\hat{E}0 = \frac{1}{1-n_1}\sum_{i=1}^{n}\frac{\left(d_i - \hat{p}(x_i)\right)y_i}{\hat{p}(x_i)} \quad (8)$$

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

3.2.2. Local Average Treatment Effect (LATE) Estimation Techniques

Another approach to impact evaluation is 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 assume 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 ***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 improved rice variety on rice productivity and total household expenditure. The first one is the simple non-parametric Wald estimator proposed by Imbens and Angrist (1994) and 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 some vector of covariates ***x*** that determine the observed outcome *y*.

To give the expressions of the Imbens and Angrist (1994) LATE estimator and that of Abadie (2003), we note that the binary variable denoting the farmer's access to improved rice varieties status is a "natural" instrument for the improved rice variety adoption status variable (which is the treatment variable here). However, firstly one cannot adopt an improved variety without having access to the seed. Secondly, it is natural to assume that access to seed affects the overall household welfare outcome indicators such as increase in yield and consumption expenditure only through adoption (i.e. the mere having access to seed of an improved variety without adopting it does not affect the welfare outcome indicators of a farmer). Hence, the two requirements for the access to the seed of an improved status variable to be a valid instrument for the adoption status variable are met.

Now, let *z* be a binary outcome variable taking the value 1 when a farmer has access to the improved variety 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 access to the seed respectively (with 1 indicating adoption and 0 otherwise).Because one cannot adopt an improved variety without having access to the seed , 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 *d1*, y_1 and y_0 (an assumption equivalent to assuming that access to seed is random in the population), then the mean impact of Improved variety adoption on sustainable rice productivity and welfare of the sub-population of improved rice varieties potential adopters (i.e. the LATE) is as given by Imbens and Angrist, 1994; Imbens and Rubin 1997, Lee, 2005:

$$E(y_1 - y_0 | d_1 = 1) = \frac{E(y|z=1) - E(y|z=0)}{E(d|z=1) - E(d|z=0)} \qquad (9)$$

The right hand side of (9) can be estimated by its sample analogue:

$$\left(\frac{\sum_{i=1}^{n} y_i z_i}{\sum_{i=1}^{n} z_i} - \frac{\sum_{i=1}^{n} y_i (1 - z_i)}{\sum_{i=1}^{n} (1 - z_i)} \right) \times \left(\frac{\sum_{i=1}^{n} d_i z_i}{\sum_{i=1}^{n} z_i} - \frac{\sum_{i=1}^{n} d_i (1 - z_i)}{\sum_{i=1}^{n} (1 - z_i)} \right)^{-1} \qquad (10)$$

which is the well-known *Wald* estimator

3.2.3. Local Average Response Function (LARF)

One of the numerous assumptions is that farmer's access to the seed of an improved variety is random; however, this is an un realistic assumption. Following Diagne and Demont (2009), Dontsop-Nguezet et.al., (2010); Awotide et.al., (2010) among many others, thus this study went further to adopt Abadie's LATE estimator which requires only the conditional independence assumption . Under this 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*) (see, Abadie, 2003; Lee 2005):

$$f(x,1) - f(x,0) = (y_1 - y_0 \mid \boldsymbol{x}, d_1 = 1) \qquad (11)$$

$$E(g(y,d,x)|d_1 = 1) = \frac{1}{P(d_1 = 1)} E(k \cdot g(y,d,x)) \qquad (12)$$

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 $f(\theta; x, d) = E(y|x, d; d_1 = 1)$ (13)

Then, using equation (7) 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*{κ (*y* − *f* (θ ; *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 (11) was 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 (12). For example, with a simple linear function $f(\theta, d, x) = \alpha_0 + \alpha d + \beta x$ where $\theta = (\alpha_0, \alpha, \beta)$ then $E(y_1 - y_0|x, d_1 = 1) = 1$. 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 sub-population of potential adopters. In the estimation below, we postulated an exponential conditional mean response function with and without interaction to guaranty both the positivity of predicted outcomes (rice productivity and welfare) and heterogeneity of the treatment effect across the sub-population of potential the improved rice varieties adopters. Because access to seed 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).

4.0. Data and Descriptive Statistics

This study focused on rice farming households randomly selected from the three major rice growing systems in Nigeria. The data were collected using multistage random sampling techniques. In the first stage, three major rice growing systems were selected. This led to the selection of upland, lowland and irrigated rice ecologies. Each of the rice ecologies has 30%, 47% and 17% share of national rice area respectively. The second stage involved the random selection of one state each from each rice producing ecologies. Hence, Kano, Osun state and Niger were selected to represent irrigated, upland and lowland rice ecologies respectively. In the third stage, two Agricultural Development Program (ADP) zones that were basically rural were purposively selected from the ADP zones in each state. The fourth stage involved the random selection of five Local Government Areas (LGAs) from each of the zones. The random selection of 3 villages from each of the LGAs constituted the fifth stage. While the last stage involved the selection of rice farming households form each of the villages. The number of rice farming households selected from each village was proportionate to size. This generated a total of 500 rice farming households. Data were collected on socio-economic/demographic characteristics, access to seed, household endowments, household expenditure, agricultural income and non-agricultural income etc.. After through data cleaning 481, representing 92.6% were finally utilized for the analysis.

The socio-economic/demographic characteristics of the farmers by adoption status are presented in Table 2. The result showed that majority (92%) of the respondents were male and 89% of the adopters and 93% of the non-adopters were male. Average age of the respondents was 46 years. The mean age of the adopters (49 years) was not significantly different from the non-adopters (46 years). In terms of educational background of the household heads, 53% of the total respondents had no formal education. The proportion with no formal education is significantly different between the adopters and non-adopters. About 33%t and 58% of the adopters and non-adopters respectively had no formal education. The proportion with primary education in the total population was 25%, while 36% and 22% of adopters and non-adopters respectively had at least primary education. About 28% of the farmers that adopted had vocational training, while only 7% among the adopter attended vocational training. Majority of the adopters (85%) had experience in upland farming, while on 18% of the non-adopters had experience in upland rice framing. Majority of the non-adopter are had experience in lowland farming.

On the overall, majority of the respondents, had farming as major occupation, also they are mainly natives of the study area and had spent an average of 42 years in the study area. The analysis further revealed that not many of the respondents had contact with extension agents either from ADP or NCRI. The household size was also large, with about 10 persons per household. This could have both positive and negative effect on households' welfare. The positive effect could arise if the large household size is used as a source of family labour, thereby reducing the cost of labour and also cut down production expenditure. However, a large household size could also worsen the poverty situation of farming household particularly if it is composed of a large number of dependants, which means the family has more mouth to feed.

Table 2: Socio-economic characteristics of respondents by Adoption Status

Variable	Pooled data (N=481)	Adopters (N=101)	Non-adopters (N=380)	Mean Difference
Gender				
% of Male	92.00	89.00	93.00	4.00
% of Female	8.00	11.00	7.00	4.00
Educational Background				
% with no formal education	53.00	33.00	58.00	25.48***
% with Primary education	25.00	36.00	22.00	13.80***
% with secondary education	20.00	31.00	17.00	14.11***
% with tertiary education	3.00	1.00	4.00	2.4
% with experience in upland rice farming	29.00	85.00	14.00	71.50***
% with experience in lowland rice farming	54.00	3.00	68.00	65.00***
% with experience in irrigated rice farming	16.00	8.00	19.00	10.76***
% of farmers that are native	80.00	78.00	81.00	23.08
% that attended vocational training	12.00	28.00	7.00	20.35
% that have farming as main occupation	84.00	51.00	92.00	39.73***
% that have access to seed	19.00	70.00	5.00	65.29***
% that have contact with ADP	13.00	8.00	14.00	6.00
% that have contact with NCRI	9.00	1.00	11.00	9.50***
Average age of household heads	46.00	49.00	46.00	3.74***
Average household size	10.00	10.00	10.00	0.59
Average years of residence in the village	41.00	42.00	41.00	1.65

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 1%

Source: Field Survey, 2009

5.0. Results and Discussion

5.1. Households Endowments by Adoption Status

Household’s endowment is usually used as a measure of wealth of the farming households and can reveal a lot about the living condition of the farming households. A well-endowed household could better adopt an improved agricultural technology than otherwise. A comparison of household assets was made between adopters and non-adopters of improved rice varieties. This was done with a view to examine if adopting improved varieties have any effect on households’ assets. The result of the analysis is presented in Table 3. Generally in the population only very few (7%) are owners of their farm land. Very few (3%) and only 8% among the adopters and non-adopters owns their farm land respectively. This suggests that access to farm land could still be a constraint to rice production and adoption of high yielding improved varieties in the study area. Rearing of animals could be an addition source of income, particularly during the off-season and can be used to argument household’s income. Farmers that have additional source of income could afford to adopt improved rice varieties consequently; the analysis revealed that about 30% of the adopters had livestock, while only 15% of the non-adopters had livestock.

Households’ assets such as radio, television, mobile phone, electricity and access to media are vital in the dissemination of information about the improved varieties which can influence adoption. Only 39% and 50% of the non-adopters and adopters have mobile phone respectively. A larger percentage of the non-adopters (57%) had access to media compare with 51% among the adopters. This implies that some of the non-adopters could be aware of the improved rice varieties through the media and yet did not adopt. In terms of access to electricity, only 47% of the non-adopters and 67% of the adopters had access to electricity. Therefore, access to electricity could be one of the constraints militating against adoption, although farmers could have radio, television but without adequate supply of electricity at the right time, they might be missing out on some important information aired when there is no light.

In addition, household’s endowments such as: house, number of rooms in the house, good sanitation, access to portable water, good roofing sheet could all combine to improve the wellbeing of all the farming households members and also encourage adoption of improved rice varieties. However, not many of the respondents were endowed in most of these assets. For instance, only 20% and 28% of the adopters and non-adopters had access to portable water. In the same vein, only 22% and 47% of adopters and non-adopters had good sanitation facility. Although many of the respondents (Over 60%) lives in their own houses, however, the adopters seems to be better-off in terms of the use of good roofing sheet as a larger percentage (66%) of them use roofing sheet as oppose to the use of thatched roof, while only 39% of the non-adopters use roofing sheet. On the overall, the adopters can be said to be well-endowed than the non-adopters.

Therefore, adoption of improved rice varieties could improve farming households' living condition through the increase in yield which can further translate into an increase in income.

Table 3: Households Endowments by Adoption Status

Household Endowments	Pooled data(N=481)	Adopters(N=101)	Non-adopters (N=380)
% that Owns of farm land	7.00	3.00	8.00
% that Owns a Mobile phone	41.00	50.00	39.00
% that owns a house	64.00	67.00	63.00
% that Owns Livestock	18.00	30.00	15.00
% that have access to portable water	23.00	20.00	28.00
% that have access to good sanitation	41.00	22.00	47.00
% that have access to media	56.00	51.00	57.00
% that used roofing sheet	45.00	66.00	39.00
% that have access to electricity	50.00	61.00	47.00
Number radio	2.00	2.00	2.00
Average number of rooms	7.00	8.00	7.00

Source: Field Survey, 2009

5.2. Determinants of Adoption

The factors that influenced adoption of improved rice varieties were examined using the binary logistic regression method. Farmers that had planted at least one improved rice varieties over a period of five years were classified as adopters and those that have engaged in the cultivation of traditional rice varieties or have adopted briefly and discontinued adoption were classified as non-adopters. The results from the logit model used to examine the factors affecting the adoption of improved rice varieties in Nigeria using maximum likelihood estimation are presented in Table 4. An additional insight was also provided by analysing the marginal effects, which was calculated as the partial derivatives of the non-linear probability function, evaluated at each variable sample mean (Greene, 1990). The log-likelihood of -43.55, the Pseudo R-square of 0.67 and the LR (Chi_2) of 176.00 (significant at 1% level), implies that the overall model is fitted and the explanatory variables used in the model were collectively able to explain the farmers' decision regarding the adoption of improved rice varieties in Nigeria. The decision to adopt improved rice varieties in Nigeria was discovered to be influenced by many socio-economic/demographic and institutional variables.

Among the variables number of years of residence in the village, access to media, access to mobile phone, vocational training, livestock, access to seed and income from other crop production significantly increased the probability of adoption. Number of years of residence in the village positively increases the probability of adoption. This could be attributed to the fact that the longer a farmer stays in a locality, the more stable and familiar with environment and this could influence adoption. Information about the improved variety increases awareness, a farmer cannot adopt a technology without being aware of it (Diagne and Demont, 2007). Access to media creates awareness and hence increases the probability of adoption. Communication about available, source, price can be passed from one farmer to the other through the use of mobile phone and this can positively influence adoption.

Vocational training as well as main occupation had a positive and significant influence on the decision to adopt improved rice variety. This is because vocational training improves the level of the farmer's knowledge and having agriculture as the main occupation will also enable the farmers to seek for productivity improved information and be more devoted to farming. Livestock is means of income diversification, and can be a source of additional income and can also be an insurance against risk and uncertainty. Possession of livestock could therefore increase the probability of adoption through its influence on income. Even though a farmer is aware of a technology, access to seed is also paramount in the adoption process. As noted by Dontsop –Nguezet et.al., access to seed is a necessary condition for the adoption of a technology. Diversification into other crops can also generate an increase in income and reduces the propensity of farming household to fall below the poverty line. Thus income from other crops can positively influence adoption.

However, contrary to a priori expectation, having agriculture as main occupation had a negative and significant effect on the adoption of improved rice varieties in the study area. This could be due to the fact that full time farmers are always missing out on information because of their long stay on the farm. Most of them occasionally do not attend trainings and also do not avail themselves of the opportunity to meet with extension agents through which Information about improved seeds could be obtained. Farming experience was also negative and significant. This implies that the propensity to adopt decreases as experience in farming, measured by the number of years put into farming activities increases. This could be due to the fact that farmers become adapted to certain ways of doing things and the tendency to adopt a new innovation is always difficult. The farmers that farm on rented land also tend to have the higher probability of adopting an improved variety. This could be attributed to the desire to achieve a higher output per hectare.

Table 4: Determinants of Improved Rice Varieties Adoption

Variables	Coefficient	Std. error	Z-value	P>|Z|	Marginal Effect
Age	0.025	0.034	0.75	0.453	0.002
residence in the village(years)	0.076**	0.034	2.25	0.024	0.004
Household size	0.021	0.097	0.22	0.825	0.001
Main occupation	-3.659***	1.114	-3.29	0.001	-0.138

Education (years)	0.052	0.076	0.68	0.496	0.003
Media	1.942**	0.749	2.59	0.010	0.012
Farming experience	-5.036***	1.717	-2.93	0.003	-0.408
Ownership of farm land	-2.510*	1.433	-1.75	0.080	-0.007
Mobile phone	4.336**	2.086	2.08	0.038	0.022
Gender	-0.344	1.698	-0.20	0.839	-0.003
Vocational training	3.941***	1.233	3.20	0.001	0.188
Livestock	2.124**	0.962	2.21	0.027	0.032
Access to seed	4.421***	0.860	5.14	0.000	0.188
Contact with Extension agents	3.144	1.464	2.15	0.032	0.105
Distance to seed source	-0.038	0.047	0.83	0.409	-0.002
Income from other crop	0.746*	0.442	1.69	0.091	0.005
Constant	-35.124	2831.48	-0.01	0.990	
Number LR chi2(18) Prob >Chi2 Log-Likelihood Pseudo R-Square	481.00 176.30 0.000 -43.53 0.6695				

5.3. Impact of Adoption on Rice Productivity and Total Household Expenditure

5.3.1. Descriptive Analysis of the Impact of Adoption

Table 4 presents the descriptive analysis of the impact of improved rice varieties adoption on income from rice production, income from other crops, total agricultural expenditure, per capita consumption expenditure, average farm size and the incidence of poverty among the farmers. The average area cultivated by all the farmers was 3.23ha, while the difference test showed that the area cultivated by the non-adopters (3.39ha) was significantly higher than that of the adopters (2.64ha). However, despite the higher area cultivated by the non-adopters, they seem not be better-off in terms of household income. For instance, the adopters had a significantly higher income from both the production of rice and other crops than the non-adopter; consequently the adopters were also able to spend more (N95151.92) on agricultural production than the non-adopters (N72215.08).

In terms of the welfare impact of improved varieties adoption, a comparison was made between the consumption expenditure of adopters and non-adopters. Per capita expenditure reflects the effective consumption of households and therefore provides information on the food security status of households. The result revealed that the consumption expenditure of the adopters (N9877.71) was higher than that of the non-adopters (N9588.92). This implies that the adopters had a better welfare than the non-adopters. The analysis of the incidence of poverty showed that about 50% of the farmers were poor. The incidence of poverty was however higher among the non-adopters (51%) than the adopters (46%). These results are consistent with other related studies on the impact of agricultural technologies on poverty (Mendola, 2007; Diagne et.al. 2009; Javier, et.al. 2010). From all the analysis above it appears the adopters were better-off than the non-adopters. However, theses comparisons did not account for the effects of other characteristics of the farmers that could influence these outcomes. Hence, these observed differences cannot be attributed entirely to the adoption of improved varieties due to the problem of selection bias and non-compliance and thus have a causal interpretation (Heckman and Vytlacil, 2005; Imbens and Angrist, 1994). We therefore employed other statistical methods to assess the impact of adoption on rice productivity and welfare.

Table 4: Descriptive Analysis of the Impact of Adoption

Variable	Pooled data	Adopters	Non-adopters	Mean Difference
Income from rice production	163537.20	184357.40	85203.73	99154***
Income from other crops	87248.44	96555.57	84823.69	11731
Non-agricultural income	81192.12	71351.33	83807.70	164.89
Total agricultural expenditure	80763.56	95151.92	77215.08	17936.83***
Per Capita Consumption Expenditure	9650.89	9877.71	9588.92	0.33
Average Farm size(ha)	3.23	2.64	3.39	0.7***
% of Poor households	50.00	46.00	51.05	6.00

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 1%

Source: Field Survey, 2009

5.3.2. Econometric Analysis of Impact of Adoption on Rice productivity

Due to the problem of selection bias and particularly non-compliance or problem of endogeneity this study we used a combination of methods to assess the impact. The impact of improved varieties adoption on rice productivity and welfare was estimated using the Local Average Treatment Effect (LATE) model. Meanwhile, for the purpose of comparison, model based on other techniques such as the Average Treatment Effect (ATE) using Inverse Propensity Score Weighting (IPSW) techniques was estimated. The LATE estimate was carried out for each of the two outcomes of interest (rice productivity and welfare) using the two different estimation methods proposed by Imbens and Angrist (1994) and Abadie (2003). The LARF estimation that is required in Abadie's method used as explanatory variables in addition to the improved varieties adoption status a set of other household characteristics to account for heterogeneity in the impact.

The LARF was also estimated using the weighted least squares procedure, in order to avoid having some of the predicted outcome to be negative.

The result of the impact of improved rice varieties adoption is presented in Table 5. The result of the mean difference showed that there was a significant difference of 165.94kg/ha in rice productivity between the adopters and non-adopters. The Average Treatment Effect (ATE) in the entire population was 249.45kg/ha, the ATE on the sub-population of adopters was 267.12. This implies that the adopters had an increase of 267.12kg/ha in rice productivity. Specifically, the LATE estimates suggested that the adoption of improved rice varieties significantly increase rice productivity by 358.89kg/ha. This could be interpreted as the change in rice productivity that is attributed to a change in improved agricultural technology status. The result revealed further that the impact was much higher among the female headed households (445.46kg/ha) than the male headed households (154.90kg/ha). Furthermore, the impact was also higher among the poor farming households (648kg/ha) than the non-poor farming households (442.78kg/ha). This implies that adoption of improved rice varieties is pro-poor in nature.

Table 5: Econometric Analysis of Impact of Adoption on Rice productivity

Estimation	parameter	Robust std. Error	Z-value
Estimation by Mean Difference			
Observed Difference	165.94*	35.68	1.66
Adopters	170.96***	63.76	8.81
Non-adopters	154.36***	66.22	10.15
Inverse Propensity Score Weighting Estimation			
ATE	249.45**	125.00	2.00
ATE1	267.12**	135.79	1.97
ATE0	220.93**	107.79	2.05
Local Average Treatment Effect Estimation			
LATE by WALD estimators	200.67	125.99	0.05
LATE by LARF	358.89***	147.22	3.22
Impact by Gender			
Male	154.90	210.25	0.06
Female	445.46***	255.07	3.67
Impact by poverty Status			
Poor	648.78***	189.00	2.64
Non-poor	442.78***	223.89	2.99

Legend: Significance level **P<0.05, *P<0.10, *** P<0.01. Source: Field Survey, 2009

Source: Field Survey, 2009

5.3.3. Econometric Analysis of Impact of Adoption on Total Household Expenditure

The empirical results of the impact of improved rice varieties adoption on welfare proxy by total household expenditure is presented in Table 7. It showed that the adoption of improved rice varieties exerted a positive and significant impact on household expenditure in Nigeria. Specifically, the LATE estimate showed that improved technology adoption significantly increased the total household expenditure by 32890.82. This represented the average change in total household expenditure brought about by the adoption of improved rice varieties. Furthermore, the result also showed the female headed households had a higher impact than the male headed households. Comparison by poverty status further revealed that the impact was pro-poor in nature as it had a significant higher impact on the poor farming households (N22573.30) than the non-poor (N14589.58). The ATE estimates also showed a positive impact just like the LATE estimates. However, the ATE estimates of the impact of improved rice varieties adoption on rice productivity and welfare do not have a causal interpretation due to the problem of non-compliance.

Table 7: Econometric Analysis of Impact of Adoption on Total Household Expenditure

Estimation	parameter	Robust std. Error	Z-value
Observed Difference	N17936.83***	4080.77	4.40
Adopters	N95151.93***	3112.59	5.60
Non-adopters	N77215.08***	2639.04	9.26
ATE	**3414***	117.96	1.67
ATE1	**8809*****	104.47	3.05
ATE0	**6428.54****	129.90	1.99
LATE by WALD estimators	26280.16**	1020.16	2.24
LATE by LARF	32890.82***	3701.00	8.90
Impact by Gender			
Male	18200.00***	3872.06	4.70
Female	24842.91***	4330.00	7.00
Impact by poverty Status			
Poor	14589.58***	1462.34	4.50
Non-poor	22573.30***	6657.26	3.39

Legend: Significance level **P<0.05, *P<0.10, *** P<0.01. Source: Field Survey, 2009

6.0. Summary, Conclusion and Policy Recommendations

This study assessed the impact of improved rice varieties on rice productivity and welfare among the rice farming households in Nigeria using different estimation techniques. Among the many findings, the result the logistic regression showed that access to seed was very important in determining adoption. Specifically, the LATE method was utilized to in order to deal with the problem of con-compliance and hence, provide a consistent estimate of the impact of adoption on our outcomes of interest. Generally, the adoption of improved rice varieties significantly impacted rice productivity and total household expenditure significantly. The impact on all the outcomes of interest was also higher among the female headed households than the male headed households. The results also showed that on the overall, the adoption of improved rice varieties was also pro-poor in nature as it had a higher positive impact on the poor households than the non-poor households in all the outcome s of interest considered in this study. In conclusion, improved agricultural technology adoption can lead to the much desired increase in productivity, ensure national and households' food security and can also be away out of the menace of rural poverty in Nigeria. Based on the above findings, the study recommended that since access to seed is a necessary condition for improved rice varieties adoption, therefore efforts should be geared toward making adequate seed available to the rural farmers in order to encourage its adoption. Since the adoption of improved rice varieties led to increase in rice productivity, then it means that one of the ways to achieve Nigeria's goal of self-sufficiency in rice production is through improved rice technology adoption, hence all necessary efforts such creation of awareness about the potential benefits inherent in the adoption of improved rice seed, increase in farmers education, more publicity about the varieties released through the media intensified. Since adoption leads to improvement in farming households' welfare, the Nigeria quest to eradicate poverty particularly among the rural dweller should incorporate strategies to increase agricultural technologies adoption as part of the components.

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