Impact of Seed Quality Improvement on Rice Productivity: Evidence from Rural Nigeria

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Abstract: Seed quality improvement has been recognised as one of the vital ways to boost agricultural productivity in developing countries, thus farmers access to seed of improved quality is expected to generate increase in yield. This study was conducted to empirically investigate the impact of seed quality improvement on rice productivity in Nigeria using a combination of approaches such as Inverse Propensity Score Weighting (IPSW) and Local Average Treatment Effect (LATE). The study used well structured questionnaire to collect a pre-intervention (2008) and post- intervention (2010) data, using multistage sampling procedure. In all, 600 rice farmers were selected based on probability proportionate to the size of rice farmers in the villages in 2008, out of which 160 farmers were randomly selected to have access to seed of improved quality (Treated) and the others did no (Control). The results revealed that the seed quality improvement impacted rice productivity significantly. Therefore, it is recommended that seed quality improvement should be incorporated into all the agricultural development programs and properly monitored for effective results.

[Awotide BA, Awoyemi TT, Okoruwa VO, Omonona BT. **Impact of Seed Quality Improvement on Rice Productivity: Evidence from Rural Nigeria.** *N Y Sci J* 2012;5(12):92-100]. (ISSN: 1554-0200). http://www.sciencepub.net/newyork. 14

Keywords: *Impact, Seed quality, Productivity, Farmers, Nigeria*

1. Introduction

Rice (Orysa zativa) has emerged as the fastest growing sector and most important staple food in Nigerian diets, especially for the urban dwellers in spite of the fact that Nigerian farmers cultivate an array of staple food crops. Rice is the only crop that is widely cultivated in all the agro-ecological zones. It is also a source of employment, particularly in the producing areas, where 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). However, local supply of rice has consistently lagged behind the national demand for rice. Consequently, Nigeria the largest country in Africa with a population of 160 million (FRN, 2006), have a very big challenge of meeting her national demand for rice despite all the available resources and the potential in rice production.

The total annual domestic rice demand is estimated to be about 5 million metric tons, whereas the annual domestic output of rice still hovers around 3 million metric tons, leaving a gap of about 2 million metric tons (Tiamiyu, 2010). The growing in the demand for rice in Nigeria has been attributed to a number of factors, notable among which is the uncontrollable population increase, which is growing at the rate of 2.8% per annum, rapid urbanization and associated changes in family occupational structure (Akpokodje et.al. 2001; UNEP, 2005). To effectively fill this demand-supply gap, the country has resorted to massive importation of parboiled rice Apart from being a drain on the hard-earned foreign exchange; rice importation also has a depressive effect on local rice production as it has shifted consumption away from local to imported rice. Thus, meeting national rice demand through local rice production is one of the major challenges confronting the nations. It has been discovered that, one way out of this predicament is to adopt intensive productivity enhancing approach, since area expansion and irrigation have already become a minimal source of output growth even at a world scale, which implies that agricultural growth will depend more and more on yield-enhancing technological change (Datt and Ravallion, 1996; Hossain, 1989).

It is believed that the adoption of new agricultural technology, such as 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). Consequently, several improved rice varieties have been developed by the national and international research institutes and disseminated to the farmers through different programs. This is based on the premise that, seed is the key to optimum use of natural resources and, according to its attributes and the breeding goal, seed determines the requirements for inputs such as pesticides, fertilizer and agricultural technology. The potential benefits which accrue to farmers from the use of good quality seed of improved varieties include enhanced productivity, better adaptation, tolerance to environmental stress, higher harvest index, reduced risks from pest and disease pressure, improved grain quality and higher profits. Hence, seed quality improvement was also pursued through the seed certification processes and some randomly selected rural farmers were granted access to the improved quality seed. Thus, farmers' use of good quality improved seed is expected to generate an increase in rice productivity, which will enhance household income and ultimately lead to poverty reduction.

2. Material and Methods

2.1. Study Area, Sampling Techniques and Data Collection

Nigeria with a population of 160 million (NBS, 2006), on al land area of 924,000 square kilometres is purely an agrarian economy. The rural economy remains largely agricultural based in a tropical climate with a variety of vegetation belts ranging from the forest in the south to the Sahel savannah in the north. Rice is grown in all agro ecological zones of Nigeria under three major production systems namely; irrigated, rain-fed upland and lowland which account for 16%, 30% and 47% respectively to the total land area devoted to rice, and they jointly contribute 97% to the national rice output (Daramola, 2005).The study used both pre-intervention (2008) and Post- intervention data (2010) collected through multistage sampling technique. Kano, Osun and Niger states were randomly selected to represent the three major rice producing systems respectively. From each of the three states, five rice producing Local Government Areas (LGAs) were selected and three villages were selected from each of the LGAs. In all, 600 rice farmers were selected based on probability proportionate to the size of rice farmers in the villages, out of which 160 farmers had access to the improved quality seed (Treated Farmers) and the others did not (Control Farmers). Data on socio-economic/demographic characteristics, treatment status, expenditure, income, and institutional variables were collected using structured questionnaire.

2.2. Analytical Framework and Estimation Techniques

2.2.1. Econometric Impact of Seed Quality Improvement on Rice Productivity

According to Rosenbaum (2001) and Lee (2005) biases that can arise when estimating causal effects are basically of two types: *overt* bias and *hidden.* Overt bias is the difference in the observed rice productivity *not* caused by the use of the good quality improved seed but which is due to differences in observed characteristics of the farmers, while hidden bias can arise as a result of the difference in the observed rice productivity not caused by the improved quality seed but which is due to differences as a result of unobservable characteristics of the farmers. Another important problem which also usually introduces bias is the problem of "non-compliance" which is also referred to as "endogenous" treatment variable problem in econometrics (Imbens and Rubin, 1997; Imbens and Angrist, 1994; Heckman and Vytlacil, 2005). The non-compliance problem arises as a result of the fact that our respondents are farmers who have the right to use the improved quality seed or not even when they had access to it. With this endogeneity, the observed increase in productivity among the treated farmers may not be due to access to the improved quality seed, but rather to the unobserved factors that cause that farmer not to stick to his or her assigned treatment. Thus the Average Treatment Effect for the entire population would be different from the mean treatment effect that would be obtained when access to the improved quality seed was randomly assigned and every farmer in the population complied with their assignment status (Imbens and Rubin, 1997; Imbens and Angrist, 1994). Hence, in order to provide a reliable impact of the improved quality seed on productivity we adopted a mixed method approach, which implies a combination of methods that will effectively eliminate all the bias.

In program impact evaluation, methods designed to eliminate biases are broadly classified into two broad categories based on the types of assumptions they require to arrive at consistent estimators of causal effects (see Imbens 2004). The methods designed to remove overt bias only are based on the "ignorability" or Conditional Independence Assumption (CIA) (Rubin, 1974; Rosenbaum and Rubin, 1983) that 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 for treated and control group (y_T and y_C). On the other hands, the pure parametric regression-based methods adopted the CIA in which the covariates are possibly interacted with treatment status variable to account for heterogeneous responses, or they are based on a two-stage estimation procedure in which the propensity score or the conditional probability of treatment $P(t = 1| x) \equiv P(x)$ is estimated in the first stage and ATE, Average Treatment Effect on the treated (ATE1) and Average Treatment Effect on the untreated (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).

2.2.2. Inverse Propensity Score Weighting Technique

The Inverse Propensity Score Weighting (IPSW) method which is a conditional independence-based estimator of ATE, ATE1 and ATE0 was adopted and are given by the following formulae (see Imbens, 2004; Lee 2005, Diagne and Demont, 2007; Dontsop-Nguezet et al., 2011):

$$A T\hat{E} = \frac{1}{n}\sum_{i=1}^{n}\frac{(t_i - \hat{p}(x_i))y_i}{\hat{p}(x_i)(1-\hat{p}(x_i))} \qquad 1$$

$$A T\hat{E}1 = \frac{1}{n_1}\sum_{i=1}^{n}\frac{(t_i - \hat{p}(x_i))y_i}{(1-\hat{p}(x_i))} \qquad 2$$

$$A T\hat{E}0 = \frac{1}{1-n_1}\sum_{i=1}^{n}\frac{(t_i - \hat{p}(x_i))y_i}{\hat{p}(x_i)} \qquad 3$$

Where n is the sample size, $n_1 = \sum_{i=1}^{n} t_i$ is the number of treated and $\hat{p}(x_i)$ is a consistent estimate of the propensity score evaluated at $\boldsymbol{x}$.

ATE= is the mean impact of the seed quality improvement in the population

ATE1=is the impact of the seed quality improvement on the subpopulation of the farmers in the treated group.

ATE0= is the impact on the subpopulation of the farmers in the control group.

A probit specification was employed to estimate the propensity score. However, the result of the ATE cannot be interpreted as the impact of the intervention, due to the fact that the ATE estimates do not correct for hidden bias (selection on unobservables). Hence, we also utilized the instrumental variable methods approach that can eliminate these problems.

2.2.3. Instrumental variable Estimation Methods

2.2.3.1. Local Average Treatment Effect Estimation Technique

The instrumental variable methods are mostly adopted to take care of the overt and hidden biases and also control for the endogeneity in the treatment. The instrumental variable (IV)-based methods was used by Heckman and Vytlacil (2005, 2007a, 2007b); Heckman et al, (1997); Card, 2001; Imbens (2004); Abadie (2003); Imbens and Angrist (1994); Diagne and Demont (2007) and Dontsop-Nguezet et al., (2011). This method involves finding a variable (instrument) that is highly correlated with program participation but is not correlated with unobservable characteristics affecting outcomes (Khandker et al., 2010). In other words, 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_T and y_C , once the effects of the covariates $\boldsymbol{x}$ are controlled for(Rubin, 1974; Rosenbaum and Rubin,1983, Diagne and Demont, 2007; Dontsop-Nguezet, 2011). Hence, being randomly assigned to receive the improved quality seed can only affects outcome via actual use of the quality seed. Therefore, to estimate the causal effect of the treatment when the compliance is not perfect, the receipt of the good quality improved seed was used as a natural choice of instrumental variable.

It is also important to note that some farmers will complier with their assignment status and other will not. However, according to Imbens and Angrist (1994) only the mean treatment effect for the subpopulation of compliers can be given a *causal* interpretation and they called such a population parameter the *local average treatment effect* denoted by LATE. Thus, LATE estimate provides the impact of seed voucher on all the outcomes with a causal interpretation. In other for IV estimate to be interpreted as the causal effect of a treatment on the compliers both monotonicity and the independence assumption must hold (Imbens and Angrist, 2004). The independence assumption requires that potential outcomes of any treatment state (y_T, y_C) are independent of the instrument z. The monotonicity assumption requires that the instrument makes every person either weakly more or less likely to actually participate in the treatment (no defiers). The monotonicity assumption is trivially satisfied in the improved seed quality case, because a farmer cannot have access to the seed without being randomly selected to receive it. Hence, the LATE estimate of the mean impact of the good quality seed on rice productivity has a causal interpretation, applies only to the subpopulation of potential user of the good quality improved seed. Specifically, the Local Average Treatment Effect (LATE) estimates the treatment effect only for those who decided to use the good quality improved seed because of a change in Z (Angrist 1994).

To give the expressions of the Imbens and Angrist (1994) LATE estimator and that of Abadie (2003), we noted that the receipt of the good quality seed is a “natural” instrument for the use of the good quality improved seed (which is the treatment variable here). Indeed, firstly one cannot use the good quality improved seed without being selected to receive it. Second, it is natural to assume that being randomly selected to receive the seed actually affect the rice productivity through the actual use of the good quality seed. This implies that being randomly selected to receive the good quality improved seed has no impact on rice productivity. Rice productivity is actually affected only when the farmers used the seed of improved quality. Hence the two vital requirement of the receipt of the improved quality seed to be a valid instrument are met. The mean impact of the improved quality seed on rice productivity of the sub-population of Compliers (i.e. the LATE) is as given by Imbens and Angrist, 1994; Imbens and Rubin 1997, Lee, 2005:

$$\hat{\lambda}_{IV\ \ \mathrm{lATE}} = E\left(y_T - y_C \mid t_1 = 1\right) = \frac{E\left(y \mid z = 1\right) - E\left(y \mid z = 0\right)}{E\left(t \mid z = 1\right) - E\left(t \mid z = 0\right)} \qquad 4$$

The denominator in equation (4) is the difference in the probability of participation in the program (probability of T=1) under the different values of the instrument. The right hand side of (4) can be estimated by its sample analog $\left(\frac{\sum_{i=1}^{n} y_i z_i}{\sum_{i=1}^{n} z_i} - \frac{\sum_{i=1}^{n} y_i (1 - z_i)}{\sum_{i=1}^{n} (1 - z_i)}\right) \times \left(\frac{\sum_{i=1}^{n} t_i z_i}{\sum_{i=1}^{n} z_i} - \frac{\sum_{i=1}^{n} t_i (1 - z_i)}{\sum_{i=1}^{n} (1 - z_i)}\right)^{-1}$ 5

This is the well-known Wald estimator. The Wald estimate gives the effect of the quality improved seed on those whose treatment status will be affected by the instrument, which is known as the Local Average Treatment Effect (LATE) (Angrist and Imbens, 1994). These are those who in the absence of the randomly assigned instrument, would not have been treated but are induced to receive treatment by the assignment. They are often referred to as the compliers. Because access to the improved quality seed is not random in the population due to the fact that farmers in the control group may one way or the other obtained the seed, thus affecting their outcomes. Also, farmers who were randomly selected to have access to the improved quality seed may eventually not use it. In addition, the access to the improved quality seed is also not randomly distributed in the population. It was targeted at rural based rice farmers and also, only farmers in the three notable rice producing ecologies were targeted for intervention. Hence, the study adopted the Abadie's estimation of LATE using the LARF, which requires the conditional independence assumption instead of the randomness assumption.

2.2.3.2. Local Average Response Function

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_T and y_C, but will become so conditional on some vector of covariates x that determines the observed rice productivity. With these assumptions, the following results can be shown to hold for the conditional mean outcome response function for potential compliers f(x,t) ≡ E(y | x, t; t_l = 1) and any function g of (y, x, t) (Abadie, 2003; Lee 2005):

$$f(x,1) - f(x,0) = (y_T - y_C \mid \boldsymbol{x}, t_l = 1) \qquad 6$$

$$E\left(g\left(y,t,x\right) \mid t_1 = 1\right) = \frac{1}{P\left(t_1 = 1\right)} E\left(k \cdot g\left(y,t,x\right)\right) \qquad 8$$

Where $k = 1 - \frac{z}{p\left(z = 1 \mid x\right)}\left(1 - t\right)$ 9

Equation (9) is a weighted function that takes the value 1 for a potential complier and a negative value otherwise. The function $f(x, t)$ is called a Local Average Response Function (LARF) by Abadie (2003). Estimation proceeds by a parameterization of the

LARF $f\left(\theta; x, t\right) = E\left(y \mid x, t; t_1 = 1\right)$ 10

Then, using equation 2 with $g\left(y,t,x\right) = \left(y - f\left(\theta; x, t\right)\right)^2$, the parameter θ is estimated by a weighted least squares scheme that minimizes the sample analogue of E\{κ (y − f (θ ; x,t))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 (8) is used to recover the conditional mean treatment effect $E\left(y_T - y_C \mid x, t_1 = 1\right)$ as a function of x. The LATE is then obtained by averaging across x using equation (8). For example, with a simple linear function $f\left(\theta, t, x\right) = \alpha_0 + \alpha t + \beta x$

Where: $\theta = \left(\alpha_0, \alpha, \beta\right)$, then $E\left(y_T - y_C \mid x, t_1 = 1\right) = \alpha$.

In this case, there is no need for averaging to obtain the LATE, which is here equaled to α. Hence, a simple linear functional form for the Local Average Response Function (LARF) with no interaction between t and x implies a constant treatment effect across the sub-population of potential compliers. In this study, we postulated an exponential conditional mean response function with and without interaction to guaranty both the positivity of predicted rice productivity and heterogeneity of the treatment effect across the sub-population of potential receivers Because, been randomly selected to have access to the improved quality seed is a necessary condition for the use of the improved quality seed, it can be shown that the LATE for the subpopulation of potential user (i.e. those with $t1$=1) is the same as the LATE for the subpopulation of actual users (i.e. those with t=$zt1$=1).

3. Results and Discussion

3.1. Socio-economic Characteristics of the Respondents

As shown in table 1, agriculture was the main occupation of the respondents as 90.0% of the respondents had agriculture as their main occupation. Because of the tediousness associated with farming, it is not a surprise that majority of the respondents (80.6%) were males, while only 19.4% were females. In terms of age distribution, a higher percentage (44.8%) of the respondents were within the age group of 41-50 years, while a negligible proportion (0.9%) were above 70.0 years of age and a total of 76.2% were between 18-50 years of age. This shows that majority of the respondents were in their active and productive age and this could have a positive influence on rice productivity. The household size was relatively higher in the study area. Majority of the respondents (76.2%) were within the household size group of 1-10 people per household. About 87.0% of the respondents were native of their respective villages and 52.0% have spent between 41-60 years in the study area. The educational background of the household's head revealed that majority of the respondents (32.0%) lacked formal education. While 15.0% had at least primary education, 10.0% had secondary education and 40.0% had Islamic education. Only 5 of the respondents, representing 0.9% had university education.

Table 1: Socio-economic/Demographic Characteristics of Respondents

Socio-Economic/Demographic Characteristics	Frequency	Percentage
Age of Household Head		
18-30	30.00	5.33
31-40	147.00	26.11
41-50	252.00	44.76
51-60	116.00	20.60
61-70	13.00	2.31
>70	5.00	0.89
Gender of Household Head		
Male	454.00	80.64
Female	109.00	19.36
Educational Background of Household Head		
No education	175.00	31.90
Primary Education	81.00	14.52
Secondary education	53.00	9.50
High education	20.00	3.58
University education	5.00	0.90
Islamic	221.00	39.61
Household size		
1-10	429.00	76.20
11-20	125.00	22.20
21-30	9.00	1.60
Main Occupation		
Farming	504.00	89.52
Non-farming	59.00	10.42
Native of the study area		
Native	491.00	87.21
Non-native	72.00	12.79
Years of residence in the village		
1-20	72.00	12.79
21-40	164.00	29.13
41-60	313.00	55.60
>60	14.00	2.49

Source: Field Survey, 2010

3.2. Descriptive analysis of the Impact of Seed Quality Improvement

The descriptive statistics was adopted to assess if there was any significant difference in the mean yield, per capita rice income and per capita consumption expenditure before and after the intervention and also between the treated and the control farmers. The significance of any observed difference was also tested using the t-test. The results presented in Table 2 revealed that there was a difference in yield of 760kg/ha significant at 1% after the intervention. In the same vein, a significant difference of ₦16077.93 and ₦ 7104 was recorded for the per capita income and per capita consumption expenditure respectively after the intervention. Furthermore, the result showed that the treated farmers had significant higher yield, per capita income and consumption expenditure of 453kg/ha, ₦ 1272 and ₦ 11147 respectively than the control farmers. Therefore, one can conclude that the use of improved quality seed had generated an improvement in the welfare of the treated farming households. However, these observed increases cannot be given any causal interpretation, because no bias was removed from the analysis, this could overestimate or under estimate the actual impact of the intervention.

Table 2: Test of Mean Difference

Variables	Before	After	Test -Mean Difference
Yield (kg/ha)	933.46	1694.26	760.00***
Per capita rice income(₦)	16575.43	32653.36	16077.93***
Per capita consumption expenditure(₦)	21218.97	28323.48	7104*
Test of mean Difference in some selected variable between Treated and Control			
Variables	**Treated**	**Control**	**Test -Mean Difference**
Yield (kg/ha)	2099.00	1663.00	435.00***
Per capita rice income(₦)	33091.00	31810.00	1272.00***
Per capita consumption expenditure(₦)	36550.00	25402.00	11147.00*

Legend: Significance level **P<0.05, *P<0.10, *** P<0.01. Source: Field Survey, 2010.

3.3. Econometric Impact Evaluation of Seed Quality Improvement

3.3.1. ***Impact of Seed Quality Improvement on Rice Productivity***

This study adopted various estimation techniques to assess the impact of seed quality improvement on rice productivity. The result of the analysis is presented in Table 3. From the result of the mean difference, it was observed that there was a significant positive difference of 435.51kg/ha in yield between the farmers that used the improved quality seed than those farmers that did not use. The result of the Inverse Propensity Score Weighting (IPSW) estimation technique showed that the mean Average Treatment Effect (ATE) on the population was 421.91kg/ha, significant at 1%. The ATE1 was 374.39kg/ha significant at 1%. Also, the ATE0 was 438.86kg/ha. However, the ATE estimates of the impact of the improved seed quality on rice productivity have no causal interpretation due to the problem of non-compliance. Consequently, in other to assess the actual impact of the intervention we adopted the LATE both by WALD estimator and the LARF. The LATE estimates by WALD estimator and LARF revealed that the use of the improved quality seed significantly increased rice productivity by 444.46 and 636.03kg/ha respectively. The disaggregation of the impact on rice productivity by socioeconomic characteristics of the farmers showed that the impact was higher among the male farmers (793kg/ha) than the female farmers (15.49kg/ha). Also, comparison across the major rice production ecologies in Nigeria revealed that the intervention had a significant positive impact across all the major rice producing ecologies in Nigeria. However, there was variation in the impact across the ecologies. The upland rice producing ecology had the highest impact of 1016.37kg/ha, followed by lowland (639.72kg/ha) and irrigated rice ecology with an impact of 594.04kg/ha. This implies that although the intervention had positive impact, the degree and the level of impact was also determined by some socioeconomic characteristics of the farmers.

3.3.2. Determinants of Rice Productivity

The determinants of rice productivity as given by the Local Average Response Function (LARF) are presented in table 4. The result showed that there were coefficients of non-interacted terms (independent variables of rice productivity) and interacted terms which are interaction between independent variable and rice productivity. The non-interacted terms showed that some other socio-economic/demographic characteristics of the farmers apart from the improved quality seed significantly explained variation in rice productivity. These socio-economic characteristics included household size, training, secondary occupation; number of years of experience in upland and lowland rice production. From the analysis, it was discovered that female headed households tend to have higher productivity than the male headed households. This could be due to the fact that the male headed households most of the time have other secondary occupations apart from farming and devotes less time and efforts into farming. Those that have secondary occupation also had higher productivity; this could probably mean that secondary occupation provides an additional income. Also as the years of experience in upland rice farming increases, rice productivity also increases. Educational background is also positively related to rice productivity, those with formal education having higher rice productivity than those without.

Furthermore the result indicated that interaction between the use of the improved good quality seed and the covariates were statistically significant (prob >F=0.000), Suggesting that the interaction had effect on rice productivity, thus confirming the presence of heterogeneity in the impact of the use of improved quality seed on rice productivity. In addition, the positive significant of the interacted terms of training, farming and years of experience in lowland rice production implies that the impact of the use of improved quality seed is higher among those farmers that had attended training before, had agriculture as main occupation and also had a higher number of years of experience in lowland rice production, while the negative significance of the interaction of secondary occupation implies that the impact of improved seed quality will be low for farmers with secondary occupation. Although not significant, the positive coefficient of the interaction term of education means that the impact on rice productivity will be higher for those farmers that were educated than the non-educated farmers.

Table 3: Impact of Seed Quality Improvement on Rice Yield

Estimation	parameter	Robust std. Error	Z-value	P>|Z|
Mean Difference				
Observed Difference	435.51***	99.45	4.38	0.000
Treated	2099.00***	86.09	24.38	0.000
Control	1663.50***	49.79	33.41	0.000
Inverse Propensity Score Weighting(IPWS) Estimates				
ATE	343.55	219.67	1.56	0.12
ATE1	515.38***	138.63	3.72	0.000
ATE0	282.27	275.86	1.02	0.31
PSB	171.83	190.13	0.90	0.37
Local Average Treatment Effect Estimation (LATE)				
LATE by WALD estimators	444.46	12599.69	0.04	0.97
LATE by LARF	636.03***	197.22	3.22	0.001
Late (by LARF) estimates by Gender, Poverty Status and Rice Ecologies				
Impact by Gender				
Male	793.84***	219.68	3.61	0.000
Female	15.49	267.43	0.06	0.95
Impact by Rice Ecologies				
Upland	1016.31***	386.43	2.63	0.000
Lowland	639.72***	223.97	2.86	0.003
Irrigated	594.04***	198.77	2.99	0.000

Legend: Significance level **P<0.05, *P<0.10, *** P<0.01

Source: Field Survey, 2010

Table 4: Estimated Coefficient of the Exponential LARF for Rice Yield

Rice Yield(kg/ha)	Coefficient	Std. Error	t-statistics
Seed voucher	6.910	0.200	34.47***
Gender	-0.028	0.105	-0.27
Household size	0.017	0.008	2.00**
Training	-0.259	0.157	-1.65*
Secondary occupation	7.737	0.097	79.89***
Main occupation	-0.141	0.103	-1.37
Experience in upland rice farming	0.016	0.005	3.38***
Experience in lowland rice farming	-0.026	0.007	-3.96***
Contact with extension agents	-0.076	0.119	-0.64
Educational background	0.107	0.075	1.42
Interacted Terms			
Gender	0.126	0.158	0.79

Household size	-0.013	0.012	-1.11
Training	0.379	0.178	2.12**
Secondary occupation	-7.656	0.153	-50.19***
Main occupation	0.311	0.158	1.97*
Experience in upland rice farming	0.007	0.008	0.96
Experience in lowland rice farming	0.025	0.009	2.54**
Contact with extension agents	-0.016	0.173	-0.09
Educational background	0.139	0.142	0.98
R-squared	0.78		
Adjusted R-squared	0.77		
Wald test for the coefficient of the non-interacted terms	8403.10***		
Wald test for the coefficient of the interacted terms	292.35***		

Legend: Significance level **P<0.05, *P<0.10, *** P<0.01
Source: Field Survey, 2010

4.0. Summary, Conclusion and Recommendations

This study provided a consistent estimate of the impact of seed quality improvement on rice productivity using mixed methods approach. Specifically, to remove selection on observable and unobservable characteristics of the farmers, we adopted the IPSW and the LATE. On the overall, this study revealed that seed quality improvement can actually generate the much desired increase in rice productivity, reduce the demand-supply gap and thereby reduce the nation over reliance on imported rice. It is therefore, recommended that seed quality improvement programs such as the seed certification processes should be encouraged and incorporated into the national agricultural development programs.

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References

1. Abadie A. Semi-parametric Instrumental Variable Estimation of Treatment Response Models. Journal of Econometrics 2003; 113: 231-263.
2. AfricaRice. Africa Rice Centre. New Rice for Africa. 2005; www.warda.org.
3. AfricaRice. Africa Rice Trends: Overview of recent developments in the sub-Saharan Africa rice sector. Africa Rice Centre Brief. Cotonou, Benin: Africa Rice Centre (WARDA). 2007;
4. AfricaRice (2009) "Increasing Investment in Africa's Rice Sector. Africa Rice Centre, Annual Report, 2009.
5. Angrist J, Bettinger E, Kremer M. Long-Term Educational Consequences of Secondary School Vouchers: Evidence from Administrative Records in Colombia". American Economic Review 2005; forthcoming.
6. Angrist J, Bettinger E, Bloom E, King E, Kremer M. Vouchers for Private Schooling in Colombia: Evidence from a Randomized Natural Experiment," *American Economic Review 2002;* 92(5): 1535-1558.
7. Awotide BA, Diagne A, Awoyemi TT, Ojehomon VET. Farm-level Constraints and Adoption of Improved Rice varieties in Nigeria. Learning Publics Journal of Agriculture and Environmental Studies 2010; 1(2), 12-29.
8. Card, D. Estimating the Return to Schooling: Progress on Some Persistent Econometric Problems. Econometrica 2001; 69(5): 1127–60.
9. Datt, G, Ravallion M. How important to India's Poor is the sectoral composition of growth. World Bank Economic Review 1996; 10 (1), 1–26.
10. Diagne A. Diffusion and adoption of NERICA rice varieties in Cote d'Ivoire. The Development Economics 2006; 44.2:208-231
11. Diagne A, Adekambi SA, Simtowe FP, Biaou G. The Impact Of Agricultural Technology Adoption On Poverty: The Case of Nerica Rice Varieties in Benin". A shorter version of the paper presented as contributed paper at the 27th Conference of the International Association of Agricultural Economists. August 16-22, 2009. Beijing, China
12. Dillion A. Access to Irrigation and the Escape from Poverty: Evidence from Northern Mali". IFPRI Discussion paper, 00782, July 2008.
13. DFID (Department for International Development). Sustainable Livelihoods Guidance Sheets.2001; www.livelihoods.org/info/info_guidanceSheets.html#6
14. Duflo, E, Glennester R, Kremer M. Using Randomization in Development Economics Research: A Toolkit". Handbook of Development Economics. Centre for Economic Policy Research (CEPR) Discussion paper No. 6059. January, 2007.

15. Galasso E, Ravallion M, Salvia A. Assisting the Transition from Workfare to Work: Argentina's Proempleo Experiment", Industrial and Labour Relations Review 2004; 57(5):.128-142.
16. Heckman J, Vytlacil E. Structural Equations, Treatment Effects, and Econometric Policy Evaluation. *Econometrica 2005;* 73 (May): 669-738.
17. Heckman J, Vytlacil E. Econometric Evaluation of Social Programs, Part I: Causal Models, Structural Models and Econometric Policy Evaluation". In *Handbook of Econometrics,* Volume 6B, J.J. Heckman, J. and E.E. Leamer (eds.), 2007; 4779-4874. Amsterdam and Oxford: Elsevier, North-Holland.
18. Heckman J, Vytlacil E. Econometric Evaluation of Social Programs, Part II: Using the Marginal Treatment Effect to Organize Alternative Econometric Estimators to Evaluate Social Programs, and to Forecast Their Effects in New Environments". In: *Handbook of Econometrics 2007b;* Volume 6B, J.J. Heckman and E.E. Leamer (eds.), 4875–5143. Amsterdam and Oxford: Elsevier, North-Holland.
19. Hosmer DW, Lemeshew S. Applied Logistic Regression". A Wiley-Inter science Publication, New York 1989.
20. Imbens G. Nonparametric estimation of average treatment effects under exogeneity: A review". Review of Economics and Statistics 2004; 86: 4-29.
21. Imbens GW, Rubin DB. Bayesian Inference for Causal Effects in Randomized Experiments with Non-compliance". Annals of Statistics 1997a; Vol. 25(1): 305-327.
22. Imbens GW, Rubin DB. Estimating Outcome Distributions for Compliers in Instrumental Variables Models". Review of Economic Studies 1997b; 64: 555-574.
23. Imbens GW, Woodridge JM. Recent Developments in the Econometrics of Program Evaluation. Journal of Economic Literature 2009; 47 (1): 5-86.
24. Imbens G, Angrist J. Identification and Estimation of Local Average Treatment Effects, Econometrica 1994; Vol. 61(2): 467-476.
25. Katz LF, Kling JR, Liebman JB. Moving to Opportunity in Boston: Early Results of a Randomized Mobility Experiment. Quarterly Journal of Economics 2001; 116(2): 607-654.
26. Khandker SR, Koolwal GB, Samad HA. Handbook on Impact Evaluation: Quantitative Methods and Practices. The World Bank, Washington.D.C. 2010.
27. Lee MJ. Micro-Econometrics for Policy, Program and Treatment Effects. Advanced Texts in Econometrics. Oxford University Press 2005.
28. 30. Mendola M. Agricultural technology adoption and poverty reduction: A propensity–score matching analysis for rural Bangladesh". Food policy 2007; 32 : 372-393.
29. 31. National Bureau of Statistics. Poverty Profile for Nigeria, 2005.
30. 32. Ogundele OO, Okoruwa VO. Technical Efficiency Differentials in Rice Production Technologies in Nigeria. AERC Research Paper,154, 2006. African Economic Research Consortium, Nairobi, Kenya.
31. 33. Ravallion M. Evaluating Anti-Poverty Programs." In Handbook of Agricultural Economics 2005; Vol. 4. R.E.Evenson and T. Paul Schultz, eds. Amsterdam: North-Holland. Available:http://info.worldbank.org/etools/docs/ Library/207006/Ravallion_Evaluating%20antipoverty%20programs_11-05.pdf.
32. Punch. Business and Economy. "Punch Newspaper, March 31, 2008 pg 15.
33. Rosenbaum PR, Rubin DB. The Central Role of The Propensity Score in Observational Studies for Causal Effects. Biometrika 1983;70(1): 41-55.
34. Rubin D. Estimating Causal Effects of Treatments in Randomized and Non-Randomized Studies. Journal of Educational Psychology 1974; 66, 688-701.
35. 38. Rubin D. Assignment to Treatment Group on the Basis of a Covariate, "Journal of Educational Statistics 1977; 2(1), 1-26.
36. Wooldridge J. Inverse Probability Weighted M-Estimators for Sample Selection, Attrition and Stratification. Portuguese Economic Journal 2002; 1, 117-139.
37. Nwabu G, Thorbecke E. Rural Development, Growth and Poverty in Africa. AERC, Plenary Sessions, December 2001 and May 2002. Journal of African Economies, Volume 13 Supplement 1, 2004. Published by: Oxford University press.
38. National Bureau of Statistics (NBS). Poverty Profile for Nigeria" Federal Republic of Nigeria. Abuja, 2006.

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