Impact of Seed Voucher System on Rice Farmers' Welfare in Nigeria: A Randomized Control Trial Approach

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Abstract

This study adopted Randomized Control Trial to examine the impact of seed voucher system on farming households' welfare in Nigeria using cross-sectional data of 600 rice farmers randomly selected from the three major rice ecologies of Nigeria. The WALD estimate reveals that the use of seed voucher increased household Per Capita Expenditure (PCE) by ₦14705.91. While the result of the Local Average Treatment Effect (LATE), shows a positive and significant impact of ₦7928.15 on PCE. Therefore, the use of seed voucher to grant farmers assess to certified improved rice seed can generate improvement in farmers' welfare if strongly pursue.

Keywords: Impact, seed; voucher; welfare; farmers; Nigeria

Introduction

Nigerian is an agrarian economy, where majority of the populace live in the rural area and depend on agriculture for food and income. About 90 per cent of Nigerian food need is produced by the small-scale farmers cultivating tiny plots of land and depend on rain-fed rather than irrigation system. Among the crops produced rice (Oryza *sativa*) occupies an important position. In the producing areas, it provides employment for more than 80.0 per cent of the inhabitants as a result of the activities that take place along the distribution chains from cultivation to consumption (Ogundele and Okoruwa, 2006). Rice is a crop with a great capacity of adaptation to the most varied conditions of climate, soil, topography and moisture and that is why its production is widespread within the country and hence, it's the only crop grown in all agro-ecological zones, from Sahel to coastal swamps.

In terms of consumption, it is the most important staple food crop in Nigerian diet. Wudiri and Fatoba (1992) and Ladebo (1999) established that Rice contributed about 12-14 per cent of the food requirement of the Nigerian population.The poorest urban households in Nigeria obtain 33 per cent of their cereal-based calories from rice. Average rice consumption expenditure represents 60 per cent of the total expenditure on cereals and 17 per cent of expenditure share on food commodities (NBS, 2004). Since mid-1970s, rice consumption has risen tremendously growing by 10.3 per cent per annum, as a result of accelerating population growth rate (2.6 per cent per annum), increasing per capita consumption, rapid urbanization and increase income levels among other factors (Akpokodje et al, 2001; Akande, 2002; UNEP, 2005).Consequently per capita rice consumption during 1980s averaged 18 kg and reached 22 kg in 1995-1999.

Nigeria requires about 5.0 million metric tons of rice to meet the domestic demand for rice, however local production can only supply 3.5 million metric tons; hence the nation depends on the international markets to fill the demand-supply gap at a colossal foreign exchange. Nigeria imported 1.4 million tons of rice equivalents to 4.8 per cent of global rice import and hence tops the list of rice importers in the year 2007(AfricaRice, 2007). The value of rice import has also increased from 60 million U.S dollars in 1990 to 288.0

million U.S dollars in 2001 and thereafter increased astronomically to 1.7 billion U.S. dollars in 2008. Apart from the negative implication of the huge rice importation on the importation of capital goods for industrial development, it also exposes the country to international shocks such as the 2008 global food crisis.

The global increase in the price of important staple food crops which started gradually in 2006, later escalated into a surge of price inflation in 2007 and 2008 and led to a global doubling of prices of major staple food crops such as rice, maize and wheat. The World Bank (2008) reported that global food prices rose 85.0 per cent over the last three years (2007-2010) and the FAO cited a 45 per cent increase in their world food price index. Rice price had climbed 74.0 per cent and maize was up 31 per cent. Generally, the high food prices hit developing countries harder, with these countries recording a 42 per cent increase over 2007, compared with 19.0 per cent for developed countries (IMF, 2008; FAO, 2008). Mostly affected among the developing countries are those that depend excessively on imported food from developed countries. For instance, Nigeria was hit by high rice price engendered by national scarcity as a result of export reduction by most of the notable international rice exporters such as India, Vietnam and U.S.A in order to meet their own local demand for rice. Some of the major consequences of the volatile food prices experienced by the developing countries are that it has the potential to spur inflationary pressures and compete for public expenditures intended for poverty alleviation or jeopardizing all the efforts to meet the Millennium Development Goal (MDG) of halving poverty by 2015 and fuelling political unrest. Also, Poorer households with a larger share of food in their total expenditures suffer the most from high food prices, due to the erosion of their purchasing power, which has a negative impact on food security, nutrition and access to school and health services. These generated serious concern across the globe particularly as it degenerated into riots and demonstrations in some African countries such as: Burkina Faso, Cameroon, Guinea, Cote d'ivoire, Mauritania and Senegal (AfriceRice, 2009). .

In order to mitigate the effects of the soaring food price on poor developing nations particularly in Sub-Saharan Africa, the Africa Rice Centre (AfricaRice), Catholic Relief Services (CRS), International Centre for Soil Fertility and Agricultural Development (IFDC) led a network of National Agricultural Organizations, Non-Governmental Organizations and local implementing partners in proposing an emergency initiative to boost rice production in Sub-Saharan Africa. Rice was focused on, because it's a major staple food crop consume in most African nations and has the potential to make the continent food secure (AfricaRice, 2008). The project was a two year project supported by United States Agency for International Development (USAID) under its Famine Funds Program. Four countries: Mali, Senegal, Nigeria and Ghana were selected for the pilot program. The project targets 10,000 farmers in each country to boost total domestic rice production by a total of 30,000 tons of paddy that is 7,500 tons per country. The program provided assistance specifically to the rice farmers in all the selected countries in four major areas: High quality seed of improved rice varieties, mineral fertilizer, and best-bet rice knowledge, post-harvest and marketing. The project also encouraged the involvement of the private sector in each country; particularly in the area of agro-input supply and also promoted the Community Based Seed Systems (CBSS).

The program built on the successful experience of the CRS and IFDC in the use of voucher system to distribute seed to farmers. (Seed vouchers are coupons or certificates with a guaranteed cash value that can be exchanged for seed from approved sellers. Seed sellers then redeemed their vouchers for cash from the issuing agency).The use of the seed voucher is based on the premise that seed is available but, subsets of vulnerable households do not have the purchasing power to obtain it and hence, the seed vouchers provided their purchasing power. Hence, from the list of the farmers that were sampled prior to the project implementation (the baseline data collected from the study area in 2008), some farmers were randomly selected to receive the seed voucher (Treated farmers); while the rest did receive the seed voucher (Control Farmers).

The use of vouchers in emergencies to provide resources to those affected by disaster has become increasingly popular since 2000, particularly for the provision of seed and other agricultural inputs. Voucher-based programmes are believed to have various advantages over the direct distribution of seed and agricultural inputs: they are said to be straightforward, timely and cost-efficient in terms of implementation, provide farmers with a choice of planting materials, strengthen farmer seed systems and local markets, offer an opportunity for farmers to test modern varieties, and also empower local communities (Longley, 2006). The achieved productivity growth can have far-reaching impacts on the productivity and growth of regional and national economies. There are several growth linkages that drive this relationship: benefits from lower food prices for urban and rural workers, more abundant raw materials for agro-industry and also for export; release of labour and capital (in the form of rural savings and taxes) to the non-farm sector; and increase rural demands for non-food consumer goods and services, which in turn support growth in the service and manufacturing sector.

Specifically, the use of seed voucher system to grant farmers access to certified improved rice seed was expected to have direct poverty reduction effects on the rice farming households through increase in rice yield which will lead to increase in farmers' income and consumption expenditure. Indirect medium and long-term poverty reduction effects are also expected as a result of improved access to education and health services brought about by increase in income. However, there is dearth of information about the impact of the project on the beneficiaries in relation to the overall farming households' welfare. Hence this study investigated the impact of the seed voucher system on farmers' welfare.

2.0. Analytical Framework and Estimation Techniques

2.1. Measurement of Welfare

This study starts by defining the appropriate welfare measure for the rice farmers. A lot of arguments and debates exit in the literature concerning the appropriate measure of welfare (see: Lipton and Ravallion, 1995;

Khan, 2000; Sahn and Stifel, 2000). However, this study in line with some other past studies on poverty and welfare in Nigeria such as Canagarajah and Thomas (2001), Okunmadewa et al (2010), Omonona (2000), Awoyemi (2011) utilized the Per Capita Expenditure (PCE) as a measure of household economic welfare. The PCE is preferred to income because it has been shown in the literature that income as a measure of welfare especially in Sub-Saharan Africa (SSA) has many drawbacks (Datt and Jollife, 1999). The PCE reveals the ability of the farming households to acquire the much needed goods and services for the betterment of households' living standard. Datt et al (2001) identified four cogent and valid reasons why it is much preferable to use the PCE rather than household income as a measure of welfare. First, according to Atkinson, 1987 income is only a measure of welfare opportunity and not welfare achievement. This is because not all income is consumed and not all consumption is financed out of income. Second, it has been found that expenditure fluctuates less than income and thus provides more accurate and stable measure of welfare. Third, respondents are more willing to give information on their expenditure than any information related to household income. Finally, where there is a large proportion of self-employed and own consumption, measurement of income is often fraught with difficulties.

2.2. Determination of the Poverty Line

Poverty line is generally defined as the per-capita monetary requirements an individual needs to afford the purchase of a basic bundle of goods and services. It is a minimum acceptable standard of the welfare indicator (Ravallion, 1992; Deaton, 1997) and it is usually adopted to classify the population into poor or non-poor. Thus, a farming household may be categorized as poor if its consumption expenditure falls below the poverty line and non-poor if it is above the poverty line. The poverty line according to Ravallion and Huppi (1991) and Kanbur, (1990) separate the poor from the non-poor. In Nigeria, official poverty line does not exist. Consequently, several poverty-related studies have adopted the relative poverty lines, which are proportions of the average PCE (Canagarajah and Thomas, 2001; FOS, 1999; Okunmadewa et al, 2010). This study also utilized the relative poverty line approach, defined as the two-thirds of the mean value of the per capita consumption expenditure among the rice farming households in the study area. Thus, households with per capita consumption expenditure below the poverty line are classified as poor and non-poor otherwise.

2.3. Measurement of Poverty Indices

There are criteria for a desirable poverty measure that are widely accepted by development economist: the anonymity, population independence, monotonicity, and distributional sensitivity principles. The anonymity principle simply means that the measure of poverty should not depend on who has the higher consumption expenditure. The population independence principle implies that the poverty measure should not depend on whether the expenditure was measure in dollar or Naira. The monotonicity principle means that if there is an addition to the expenditure of someone below the poverty line, all other expenditure held constant, and poverty can be no higher than it was. The distributional sensitivity principle states that, other things equal, the transfer of expenditure from a poor person to a non-poor person will make the population poorer. The standard Foster-Greer-Thorbecke (FGT) (1984) often refers to as the P_α class of poverty measures employed to generate the poverty profile of the respondents before and after the project for the two groups (the treatment and the control group) satisfy all the four criteria. The FGT takes the form;

$$P_\alpha = \frac{1}{n}\sum_{i=1}^{n} q\left[\frac{Z - Y_{pi}}{Z}\right]\alpha \qquad 1$$

Where Z = the poverty line

q= number of individual below the poverty line

n = number of individuals in the reference population

Y_{pi} = per capita consumption expenditure of the i^{th} household

α = FGT index which takes values 0, 1, 2.

$Z-Y_i$ = poverty gap of the i^{th} household

$\frac{Z-Y_i}{Z}$ = poverty gap ratio

This class of poverty measure is flexible in two ways. One, α is a policy parameter that can be varied to approximately reflect poverty "aversion" and two, the P_α class of poverty indices is sub-group decomposable.

When α = 0 in equation (1)

P_o = 1/n (q) = q/n = H 2

The head count is the number of people in a population who are poor, while the headcount ratio (H) is the fraction of the population who are poor. The poverty gap measures the total amount of money necessary to raise everyone who is below the poverty line up to that line, When α = 1, the poverty measure becomes the poverty-gap index (PG)

$$P_{\alpha=1} = PG = \frac{1}{n}\sum_{i=1}^{n} q_i\left[\frac{Z - Y_{pi}}{Z}\right] = HI \qquad 3$$

$$\text{Where } I = \frac{1}{q}\sum_{i=1}^{n} q\left[\frac{Z - Y_{pi}}{Z}\right] = HI \qquad 4$$

is the expenditure gap ratio. I is the mean of the poverty gaps expressed as a portion of the poverty line. This measure is insensitive to income distribution among the poor.

When α = 2, the squared poverty gap index (SPG) is generated given by,

$$P_{\alpha\text{-}2} = SPG = \frac{1}{n}\sum_{i=1}^{n} q_i \left[\frac{Z - Y_{pi}}{Z}\right]^2 \qquad 5$$

$P_{\alpha\text{-}2}$ measure is increasingly used as a standard poverty measure by the World Bank, the regional development banks, most United Nation agencies and it is used in, most empirical work on poverty because of its sensitivity to the depth and severity of poverty. The incidence is measured by the number of people in the total population living below the poverty line while the poverty intensity is reflected in the extent to which the incomes of the poor fall below the poverty line.

Another advantage of the P_α measure is that it is decomposable by population subgroups. That is :

$$P_\alpha = \sum_{j=1}^{m} K_j P_{\alpha j} \qquad 6$$

Where:

j =1,2,3…….m, k_j is the population share of each group, $P_{\alpha j}$ is the poverty measure of group j. The contribution of each group C_j to overall poverty can be calculated as follows:

$$C_j = \frac{K_j P_{\alpha j}}{P_\alpha} \qquad 7$$

This property of the index implies that when any group becomes poor, aggregate poverty will increase. Hence poverty can be disaggregated by subgroup such as gender and region.

2.4. Econometric Analysis of the Impact of Seed Voucher System on Welfare

Most existing impact assessment evaluation techniques were developed to minimize or eliminate the biases in evaluation techniques. In the treatment effect literature biases that can arise when estimating causal effects are of two types (Rosenbaum, 2001; Lee, 2005): *overt* bias and *hidden* bias. Overt bias is the difference in the observed welfare outcome *y* not caused by the receipt of the seed voucher but which is due to differences in observed characteristics of the farmers. Hidden bias is the difference in the observed welfare outcome *y* not caused by the seed voucher but which is due to differences as a result of unobservable characteristics of the farmers. A third problem is the problem of "non-compliance" also called the "endogenous" treatment variable problem in econometrics (Imbens and Rubin, 1997; Imbens and Angrist, 1994; Heckman and Vytlacil, 2005). The non-compliance problem arises because the subjects of treatments are people who may or may not stick to their assigned treatments even if the treatment was assigned randomly. Consequently, the difference in an individual farmer's potential welfare outcome may not be due to the seed voucher but rather to the unobserved factors that cause that farmer not to stick to his or her assigned treatment. As a result, the ATE for the entire population is different from the mean treatment effect that would obtain when the seed voucher was randomly assigned and every farmer in the population complied with their assignment (Imbens and Rubin, 1997; Imbens and Angrist, 1994).

The simplest way to assess the impact of the seed voucher given RCT is by examining the differences in mean outcomes of treated and control farmers or by using simple regression procedures that include the treatment status variables among the set of explanatory variables. Critics have pointed out that such simple procedures are flawed because they fail to deal appropriately with the self-selection bias and selection on unobservable (Imbens, and Wooldridge, 2009; Heckman and Vytlacil, 2005; Lee, 2005; Imbens, 2004; Rosembaum, 2002; Heckman and Robb, 1985; Rosembaum and Rubin, 1983; Rubin, 1974). Some studies also used the propensity score matching (PSM) method to deal with the self-selection bias problem and estimate the *average treatment effect (ATE* (Mendola, 2007; Mojo *et al.*, 2007 and Javier and Awudu, 2010). Some of them combine both the PSM with the Double Difference (DD) methods (Oni et. al., 2007; Mkonya et. al., 2007). However, the PSM method fails to deal appropriately with the selection on unobservable problem which may be handled by the DD. But, the two approaches do not deal appropriately with the problem of non-compliance.

2.4.1. Inverse Propensity Weighting (IPSW) Estimation of Average Treatment Effect

The methods that have been adopted in the 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 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). The methods designed to remove overt bias only 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_T and y_C. 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 $P(t = 1| x) \equiv P(x)$ (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).

The conditional independence-based estimators of ATE, ATE1 and ATE0 that was adopted are the so-called inverse propensity score weighing estimators (IPSW), which are given by the following formulae (see Imbens, 2004; Lee 2005; Diagne and Demont 2007):

$$AT\hat{E} = \frac{1}{n}\sum_{i=1}^{n}\frac{(t_i - \hat{p}(x_i))y_i}{\hat{p}(x_i)(1-\hat{p}(x_i))} \qquad 8$$

$$A T\hat{E}1 = \frac{1}{n_1}\sum_{i=1}^{n}\frac{\left(t_i - \hat{p}(x_i)\right)y_i}{\left(1-\hat{p}(x_i)\right)} \qquad 9$$

$$A T\hat{E}0 = \frac{1}{1-n_1}\sum_{i=1}^{n}\frac{\left(t_i - \hat{p}(x_i)\right)y_i}{\hat{p}(x_i)} \qquad 10$$

Where n is the total number of respondents (sample size), $n_1 = \sum_{i=1}^{n} t_i$ is the number of treated farmers 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 voucher in the population

ATE1=is the impact of the seed voucher on the subpopulation of the farmers in the treated group

ATE0= is the impact on the subpopulation of the farmers in the control group. This is equally of interest in case the program is to be extended to those farmers who currently did not receive the seed voucher.

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. The ATE estimates do not correct for hidden bias (selection on unobservables)which is due the fact that farmers decision to receive the seed voucher could be based on some anticipated benefits and problem of non-compliance or endogeneity which may arise as a result of the fact that the farmer can decide to receive the seed voucher or not . Hence it is necessary to use other methods that can eliminate these problems; this study therefore employed the Local Average Treatment Effect (LATE) estimation technique to provide a consistent estimate of the seed voucher impact on farmers' welfare.

2.4.2. Local Average treatment Effect (LATE) Estimation Technique

The realization of a consistent estimate of the impact of a project on an outcome of interest depends on the use of an appropriate model. The choice of the appropriate model to use in any impact evaluation study however, depends on how the treatment under investigation was disseminated and received by the intended beneficiaries. In the case of this study, the seed voucher system was implemented in few randomly selected states .This means that the overall population of Nigerian rice farmers were not equally exposed to the program (that is the instrument was not randomly distributed). On the other hand, rice farmers that were randomly selected to receive the seed voucher had full control over their decision to receive it or not (the receipt of the instrument is endogenous). Therefore following the impact assessment literatures, the most plausible assumption in this case is that of selection on unobservable (Imbens, and Wooldridge, 2009; Diagne, *et al.*, 2009). This is because farmers' decision to receive the seed voucher even thou they were randomly selected to receive is based on the anticipated benefit they would derive by receiving it. However this anticipated benefit cannot be observed, hence the need for an instrument which will be independent of welfare and could only affect welfare through the receipt of the seed voucher.

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) to deal with overt and hidden biases and also deal with the problem of endogenous treatment. The 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). The methods rely on finding a variable excluded from the outcome equation but which is also a determinant of programme participation. It is often the case in social experiment that some of those randomly selected for the programme do not want to participate. Hence, being randomly assigned to receive the seed voucher only affects outcome via actual receipt of seed voucher.

In Random experiments non-compliance with treatment status has been identified to be one of the major problems that could bias the estimate. Imbens and Angrist (1994) solve the problem of non-compliance in the population by dividing the population into four groups based on compliance status: *compliers* (those who adhere to their assigned treatment), *always takers* (those who manage to always take the treatment regardless of their assignment), *never takers* (those who never take the treatment regardless of their assignment) and *defiers* (those who do the opposite of what their assignment asked them to do). The important point made by Imbens and Angrist (1994) is that 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.

Because the receipt of seed voucher is a farmer's choice even when they were randomly selected to receive it, this led to the problem of non-compliance or endogenous treatment problem discussed above. Therefore, the ATE estimate of the impact of the seed voucher on poverty indicators, have no causal interpretation. Thus, we need the LATE estimate in order to have an estimate of the impact of seed voucher on all the outcomes with a causal interpretation. The monotonicity assumption is trivially satisfied in the seed voucher case because one cannot receive the seed voucher without being randomly selected to receive it. This effectively rules out the cases of *defiers* and *always takers*. Thus, for assessing the impact of the seed voucher on any farmer's outcome, the population was partitioned into only two distinct groups: the group of compliers, which is the group of potential receivers (those who will receive the seed voucher when they are randomly selected to receive it), and the group of never takers, which is the group of farmers that will never receive it even when they are assigned to receive it . Hence, the LATE estimate of the mean impact of seed voucher on all the outcomes of interest has a causal interpretation, applies only to the subpopulation of potential receivers of the seed voucher.

Specifically, the Local Average Treatment Effect (LATE) estimates the treatment effect only for those who decide to participate because of a change in Z (Angrist 1994). This study adopted 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 t, and an instrument z. 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. i.e. $\left[y_{iT}, y_{iC}, T_i(1), T_i(0)\right]$is independent of 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) i.e. $T_i(1) \geq T_i(0)$ for all i.

To give the expressions of the Imbens and Angrist (1994) LATE estimator and that of Abadie (2003), we note that the random assignment is a "natural" instrument for receipt of seed voucher e (which is the treatment variable here). Indeed, firstly one cannot receive the seed voucher without being randomly selected to receive it. Second, it is natural to assume that being randomly selected to receive the seed voucher actually affect the farmers' welfare only through the receipt of the seed voucher. That is being randomly selected have no impact on welfare outcome. The welfare of the farmers is actually affected only when the farmers received the seed voucher. Hence the two vital requirement of the random assignment to be a valid instrument are met. Therefore, the mean impact of the seed voucher on welfare of the sub-population of Compliers (i.e. the LATE) is as given by Imbens and Angrist, 1994; Imbens and Rubin 1997, Lee, 2005:

$$\hat{\lambda}_{IV\ \text{lATE}} = E\left(y_T - y_C \middle| t_1 = 1\right) = \frac{E(y|z=1) - E(y|z=0)}{E(t|z=1) - E(t|z=0)} \qquad 11$$

The denominator in equation (11) 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 (11) can be estimated by its sample analogue:

$$\left(\frac{\sum_{i=1}^{n} y_i z_i}{\sum_{i=1}^{n} z_i} - \frac{\sum_{i=1}^{n} y_i (1-z_i)}{\sum_{i=1}^{n} (1-z_i)}\right) \times \left(\frac{\sum_{i=1}^{n} t_i z_i}{\sum_{i=1}^{n} z_i} - \frac{\sum_{i=1}^{n} t_i (1-z_i)}{\sum_{i=1}^{n} (1-z_i)}\right)^{-1} \qquad 12$$

This is the well known Wald estimator. The Wald estimate gives the effect of the treatment 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 in impact assessment literature.

Because the receipt of the seed voucher is not random in the population due to the fact that farmer in the control group may one or the other obtained the seed voucher thus affecting their welfare. Also, farmers who were randomly selected to receive the seed voucher may eventually not receive it. In addition, the received of the seed voucher 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.

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 outcome y. 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_1 = 1) and any function *g* of (*y*, *x*, *t*) (Abadie, 2003; Lee 2005):

$f(x,1) - f(x,0) = (y_T - y_C \mid \boldsymbol{x}, t_1 = 1)$ 13

$$E\left(g(y,t,x)\middle|t_1=1\right)=\frac{1}{P(t_1=1)}E\left(k\cdot g(y,t,x)\right) \qquad 14$$

Where $k=1-\dfrac{z}{p\left(z=1\middle|x\right)}(1-t)$ 15

Equation (15) 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 $f(\theta;x,t)=E\left(y\middle|x,t;t_1=1\right)$ 16

Then, using equation (9) with $g(y,t,x)=(y-f(\theta;x,t))^2$, 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 (13) is used to recover the conditional mean treatment effect $E\left(y_T-y_C\middle|x,t_1=1\right)$ as a function of *x*. The LATE is then obtained by averaging across *x* using equation (14)

For example, with a simple linear function $f(\theta,t,x)=\alpha_0+\alpha t+\beta x$

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

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 farmers' welfare and heterogeneity of the treatment effect across the sub-population of potential receivers (Those who will receive the seed voucher when randomly selected to receive). Because been randomly selected to receive the seed voucher is a necessary condition for the receipt of the seed voucher, it can be shown that the LATE for the subpopulation of potential receiver of seed voucher (i.e. those with $t1$=1) is the same as the LATE for the subpopulation of actual receiver of the seed voucher (i.e. those with t=$zt1$=1).

3.0. Data and Descriptive Statistics

The study used both baseline data (2008) and Post-voucher data (2010) collected by AfricaRice/NCRI through multistage sampling technique. Osun, Niger and Kano states were purposively selected to represent the three prominent rice producing systems-upland, lowland and irrigated 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 to generate a total of 45 villages. 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 received the seed voucher (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. Data were analyzed using descriptive statistics, Foster-Greer-Thorbecke (FGT) poverty measure and Inverse Propensity Score Weighting Technique and Local Average Treatment Effect (LATE). After data cleaning, 563 were used for the analysis.

As shown in table 2, agriculture was the main occupation of the respondents as 90.0 per cent 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 per cent) were males, while only 19.4 per cent were females. In terms of age distribution, a higher percentage (44.8 per cent)of the respondents were within the age group of 41-50 years, while a negligible proportion (0.9 per cent) were above 70.0 years of age and a total of 76.2 per cent 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 per cent) were within the household size group of 1-10 people per household. About 87.0 per cent of the respondents were native of their respective villages and 52.0 per cent 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 per cent) lacked formal education. While 15.0 per cent had at least primary education, 10.0 per cent had secondary education and 40.0 per cent had Islamic education. Only 5 of the respondents representing 0.9 per cent had university education.

4.0. Results and Discussion

4.1. Descriptive Analysis of the Impact of Seed Voucher on Yield, Rice Income and PCE

This section presented a descriptive analysis and test of mean difference of some selected variable. The result of the analysis is presented in table 3. The result shows that the yield, per capita income from rice production, and per capita consumption expenditure increased significantly after the intervention. The average yield of rice before the intervention was 933.46kg/ha, this increased tremendously to 1694.26kg/ha. In the same vein per capita rice income and per capita consumption expenditure also experience a significant increase. The result of the t-test also revealed that these observed increase were statistically significant at different levels. This implies that the living standard of those farmers that received the seed voucher significantly improved after the intervention. However, this observed improvement cannot be attributed solely to the seed voucher. This is because, without knowing why some farmers received the seed voucher, while others did not (even when they were randomly selected to receive it), such a comparison may be deceptive and has no causal interpretation.

4.2. Poverty Profile of the Respondents

The poverty profile of the respondents was constructed in order to describe their pattern of poverty. The aim of the poverty profile is to bring to limelight the main facts on poverty among the respondents. Hence the pattern of poverty was examined to see how it varies by gender, state and main occupation and also examined how the receipt of seed voucher has impacted on the poverty indices. Analysis of poverty among the population of the sampled farmers as shown in table 4, shows that before the intervention, the incidence, depth and severity of poverty were 57.33 per cent , 27.37 per cent and 17.11 per cent respectively. However, after the intervention, the analysis shows a reduction in all the poverty indices. In terms of percentage, the seed voucher generated 23.41 per cent, 26.28 per cent and 34.48 per cent reduction in the incidence, depth and severity of poverty respectively after the intervention.

The disaggregation of poverty profile by gender is presented in table 5. The result shows a remarkable reduction in all the indices after the intervention. Among the male headed households for instance, there was a 32.89 per cent, 37.61 per cent and 46.48 per cent reduction in poverty incidence, depth and severity respectively after the intervention. In the same vein, the female headed households also experience a similar reduction of 45.26 per cent, 49.39 per cent and 46.59 per cent in poverty incidence, depth and severity after the intervention. The analysis of the poverty profile by state is presented in table 6. The result reveals that all the poverty indices also experienced a reduction, particularly in Niger state where the proportion of population below the poverty line before the intervention was almost halved after the intervention. In most poverty studies in Nigeria, it has been reported that poverty is prevalent among the rural farming households. However, with the seed voucher had a significant poverty reduction impact on those households that have farming as a major occupation. This is shown in table 7.

4.3. Econometric Analysis of Impact of Seed Voucher on Welfare

4.3.1. Average Treatment Effect (ATE) Estimates

Prior to the estimation of the ATE, the mean difference in the welfare outcome was first calculated. This was done in order to obtain firsthand information about the impact of the seed voucher on welfare given randomization of the assignment. The mean difference shows that there was a positive and significant difference in per capita household expenditure of ₦13565.83 between the farmers that received the seed voucher and those that did not. This implies that the receipt of the seed voucher that granted farmers access to certified improved rice seed at a subsidized rate has on the average added ₦13565.83 to the per capita household expenditure of the rice farmers in the treated group.

The Average Treatment Effect of the receipt of the seed voucher was calculated using various Ordinary Least Square and Inverse Propensity Score Weighting estimation techniques. The result of the estimation is presented in table 8. The result of the parametric OLS estimation shows a positive and significant (₦13561.22) Average Treatment Effect of the seed voucher on the sub population of the farmers that received the seed voucher (ATE1). The results of the other parameters such as ATE (N4352.72), ATE0 (N1068.82) were also positive but not significant. Furthermore, the study also adopted the IPSW estimation that relies on attaching weight to each household using the propensity score. The analysis shows a positive and significant impact of ₦13982.10 on the sub-population of treated farmers (ATE1). While the impact in the population (ATE) and on subpopulation of the farmers in the control group (ATE0) was positive although not significant.

However, all the above estimations do not have causal meaning due to the problem of non-compliance associated with the program. Although some of the farmers were randomly selected to receive the seed voucher, they still have the right to decide whether to receive it or not. Hence, introducing non-compliers into the intervention. This necessitated the use of the Local Average Treatment Effect estimation technique to actually isolate the impact of the intervention on the subset of farmers that actually collected the seed voucher after been randomly selected to receive it.

4.3.2. LATE Estimate of the Impact of Seed Voucher on PCE

The per capita household expenditure of the farmers was used as proxy for welfare. The study consistently estimates the impact of seed voucher per capita expenditure (PCE) using the *Local Average Treatment Effect* (LATE). The LATE estimation on PCE was done by using two different estimation methods proposed by Imbens and Angrist (1994) and Abadie (2003). Both methods use the instrumental variable approach to solve the selection bias and non-compliance problems.

The LATE estimation method proposed by Imbens and Angrist (1994) assumes that the instrumental variable is random in the population. However, the method proposed by Abadie (2003) does not require this strong assumption; it rather adopted the *Local Average Response Function* LARF which uses as explanatory variables (in addition to the treatment status variable) a set of farmers' socio-economic and demographic characteristic variables. Moreover, to account for heterogeneous impact, the treatment status dummy variable is interacted with some of the covariates *x.* Furthermore, the study estimated an exponential LARF (using a nonlinear weighted least squares procedure) to avoid having some of the predicted values of the reported PCE to be negative (for details, see Imbens and Wooldridge, 2008; Lee, 2005 or Imbens, 2004).

The result of the impact of the seed voucher on the per capita household expenditure was calculated using various estimation techniques, such as the Mean difference, the Parametric (OLS) and LATE (WALD and LARF). As shown in table 9, the result of the LATE using the WALD estimator shows that the receipt of seed voucher has added as much as ₦147905.91 to the per capita household expenditure of the farmers who received the seed voucher because they were randomly selected to receive it. These farmers are referred to as the compliers. However, to further confirm the true impact of the intervention. The assumption of randomness of the instrument was relaxed. Consequently, the study went further to calculate the LATE by adopting Abadie's LARF. The result of the LARF shows that seed voucher has a positive and significant impact of ₦7928.15 on the per capita household expenditure.

4.3.3. LATE Estimate of the Impact of Seed Voucher on PCE by Gender, Poverty Status and by State.

Using the LARF, the impact of the seed voucher on farmers' welfare was calculated by gender, poverty status and by state. The impact by gender shows that the project has a significantly positive impact of ₦13092.21 on the male headed households, while a positive but insignificant impact was discovered on the female headed households. A lot of factors could be responsible for this. The farm size of the female headed households (1.9ha) was relatively smaller compare with the male headed households (2.5).This could have effect on the output and consequently reduce the income.

The analysis went further to disaggregate the impact by state with a view to examine the differential impact across the three selected states. The intervention has positive and significant impact in all the three states however the magnitude of the impact differs. Kano state has the highest impact of ₦24762.00 followed by Osun (₦18883.50) and the lowest impact was recorded in Niger state (₦7543.25). This could also be due to the pre-existing status of the state in terms of poverty. Osun is the in the south-western Nigeria where poverty is reported to be lowest. While Niger and Kano state are both in the North central and north-north zone of the country and poverty is a major issue in these states. In terms of impact by poverty status, a positive and significant impact was recorded for the non-poor farming households, while it has an insignificant positive impact on the poor farming households.

4.3.4. Determinants of Per Capita Household Expenditure

The determinants of household per capita expenditure as given by the LARF are presented in table 10. This table clearly reveals that some other socioeconomic characteristics of the farmers apart from the seed voucher also have significant effect on the per capita household expenditure. These variables include gender, main activity, training and contact with extension agents. The coefficient of gender is negative and statistically significant (P>0.10), this implies that the female headed households have a higher per capita expenditure than the male headed households. Furthermore, having farming as main occupation is also positive and significantly related to the household's per capita expenditure. Training is also positive and significantly related to the' per capita household expenditure. Those farmers that have attended training before were opportune to learn new production techniques that can have positive impact on output and consequently the farmers' income would increase, with its attendant positive effect on the household's per capita expenditure.

However, the interaction between the independent variables and the treatment variable shows that there was heterogeneity in the treatment. The result of the Wald test of the interacted and non-interacted terms is statistically significant. This shows that there was interaction between the covariates and the treatment variable and also suggested that interactions have a significant effect on the per capita household expenditure. For example, the coefficients of the interacted term for gender, and educational background of the household head was positive and statistically significant (P>0.10), this implies that the impact of the seed voucher will be higher for the female headed and educated households. Meanwhile, the coefficient of the interacted term for main occupation is negative and statistically significant (P>0.01), the implication is that, the impact of seed voucher on household per capita expenditure will be lower among those households that have farming as main occupation. The reason could be due to the fact that, although farming households were originally targeted to receive the seed voucher, most of those randomly selected did not eventually received it and also among those that received the seed voucher, not of them used it to collect seed for planting.

5.0. Summary, Conclusion and Policy Recommendation

This study assessed the impact of seed voucher on rice farmer's welfare. The analysis of poverty before and after the intervention shows that poverty significantly reduced in the population after the intervention. Specifically, there was a reduction in poverty by gender, state and also by main occupation. The result of the ATE estimations also reveals that there was significant impact on the PCE of the sub-population of treated farmers. Due to the problem of non-compliance in program impact evaluation, particularly when RCT is adopted, therefore, in order to consistently estimate the impact of the seed voucher on welfare of the farmers, the study went further to adopt the LATE. The result of the LATE by WALD shows a positive impact of ₦14705.91 on PCE. Using the LARF, a positive and significant impact of ₦7928.15 on PCE was recorded.

From the foregoing it can be concluded that the use of seed voucher to grant farmers assess to certified improved rice seed can generate the much required improvement in living standard of the farming households. Therefore, it is recommended that seed voucher system should be adopted to grant farmers access to seed at the right time. Also, the use of certified improved rice seed should be promoted among the rice farmers in order to achieved the goal of self-sufficiency in rice production and also for possible export which can diversify the economy base of the country and reduce the over reliance on the oil sector.

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Appendix

Table 1: Definition of variables

Variables	**Type**	**Description of variables**
Poor	Dummy	1 if a farmer is poor and 0 otherwise
Seed voucher	Dummy	1 if farmer received seed voucher, 0 otherwise
Demographic Variable		
Age	Continuous	Age of household head in years
Household size	Continuous	Number of people in the household
Gender	Dummy	1 if household head is male, 0 otherwise
Socio-economic variables		
Farm size	Dummy	Size of a farmer's farm land in hectare
Education	Continuous	Number of years of education of household head
Years of farming experience	Continuous	Number of years of experience in rice farming
Main occupation	Dummy	1, if farming , 0 otherwise
Secondary activity	Dummy	1, if a farmer has secondary occupation and 0, otherwise
Income from agricultural production	Continuous	The total household income from agricultural production
Farm size	Continuous	Size of farm land in hectare
Institutional variables		
Contact with extension agents	Dummy	1 if a farmer has contact with extension agents , 0 otherwise
Training	Dummy	1 if farmer has attended training organized by research institute, 0 otherwise

Table 2: 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.

Table 3: Test of Mean Difference

Variables	Before	After	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*
Variables	**Treated**	**Control**	**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

Table 4: Poverty Profile of all Treated Farmers

Statistics	Before (%)	After (%)	Percentage Reduction
Head count	57.33	43.91	23.41
Poverty depth	27.37	20.37	26.28
Poverty severity	17.11	11.21	34.48

Source: Field Survey, 2010.

Table 5: Poverty Profile of the Treated Farmers by Gender

	Statistics	Before (%)	After (%)	Percentage Reduction
Male	**Head count**	61.07	40.98	32.89
	Poverty depth	29.46	18.38	37.61
	Poverty severity	18.18	9.73	46.48
Female	**Head count**	57.69	31.58	45.26
	Poverty depth	29.72	15.04	49.39
	Poverty severity	18.16	9.70	46.59

Source: Field Survey, 2010.

Table 6: Poverty Profile of the Treated Farmers by State

	Statistics	Before (%)	After (%)	Percentage Reduction
Osun	**Head count**	39.62	31.25	21.13
	Poverty depth	21.58	15.41	28.59
	Poverty severity	14.79	8.74	40.91
Niger	**Head count**	76.59	47.06	38.56
	Poverty depth	29.16	19.75	32.27
	Poverty severity	13.86	10.09	27.20
Kano	**Head count**	58.00	53.06	8.52
	Poverty depth	32.63	25.89	20.66
	Poverty severity	22.62	14.80	34.57

Source: Field Survey, 2010.

Table 7: Poverty Profile of the Treated Farmers by Main Occupation

	Statistics	Before (%)	After (%)	Percentage Reduction
Non-Farming	**Head count**	37.50	25.00	33.33
	Poverty depth	21.02	6.85	14.17
	Poverty severity	12.95	2.45	81.08
Farming	**Head count**	58.45	45.00	23.01
	Poverty depth	28.01	21.14	24.53
	Poverty severity	17.34	11.71	32.47

Source: Field Survey, 2010.

Table 8: Average Treatment Effect (ATE) Estimates of the Impact on PCE

Estimation	parameter	Robust std. Error	Z-value
Mean Difference			
Observed Difference	13565.83**	5245.67	2.59
Treated	50520.71***	4026.98	12.55
Control	36954.88***	3361.61	10.99
ATE Estimation with parametric Functional Form(OLS)			
ATE	4352.79	8966.23	0.49
ATE1	13561.22*	7954.59	1.70
ATE0	1068.82	10654.62	0.10
ATE Estimation with Inverse Propensity Score Weighting (IPSW)			
ATE	9410.00	8434.96	1.12
ATE1	13982.10***	4585.05	3.05
ATE0	7779.59	10750.82	0.72

Source: Authors' calculation

Table 9: Impact of Seed Voucher on Per Capita Household Expenditure

Estimates	parameter	Robust std. Error	Z-value
LATE by WALD estimators	14705.91	96563.31	0.51
LATE by LARF	7928.15*	4256.88	1.86
LATE by LARF estimates by gender, Poverty Status and State			
Impact by Gender			
Male	13092.21**	5277.63	2.48
Female	1320.58	229.42	0.57
Impact by poverty Status			
Poor	4833.43	4887.79	0.99
Non-poor	11870.88***	4361.15	2.72
Impact by State			
Osun	7543.25*	4026.26	1.87
Kano	24762.00**	9828.34	3.09
Niger	18833.50***	6102.03	2.52

Legend: Significance level *10%, **5%, and ***1%

Source: Field Survey, 2010

Table 10: estimated coefficient of the LARF for Per Capita Expenditure

Per Capita Household Expenditure	Coefficient	Standard Error	T-statistics
Coefficients of the non-interacted terms			
Seed voucher	10.68	0.76	14.11***
Gender	-0.45	0.23	-2.00**
Main activity	11.25	0.55	20.31***
Training	0.54	0.32	1.69*
Age	-0.01	0.01	-0.31
Educational Background	-0.21	0.19	-1.05
Farm size	-0.01	0.06	0.00
Contact with extension Agents	-0.56	0.32	-1.71*
Coefficients of the interacted terms			
Gender_seed voucher	0.83	0.43	1.94*
Main activity_seed voucher	-11.54	0.62	-18.50***
Training_seed voucher	0.18	0.39	0.45
Age_seed voucher	-0.01	0.02	-0.50
Educational background_seed voucher	0.80	0.47	1.70*
Farm size_seed voucher	-0.07	0.11	-0.65
Contact with extension agents_seed voucher	0.35	0.42	0.84
R-squared Adjusted R-squared Wald test for the joint significant of all coefficient Wald test for non-interacted terms	0.31 0.29 17481.67*** 189.94***		

Source: Field Survey, 2010