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Ex post impact of farmers' adoption of Root and Tubers Expansion Program (RTEP) on yield

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This paper evaluates the *ex post* impact of farmers' adoption of Root and Tubers Expansion Program (RTEP) on yield, crop income and poverty in rural Nigeria by means of primary data collected from 161 households in 3 local government areas in South West Nigeria. Using FGT poverty measures and propensity score matching techniques the study found that poverty incidence is higher by about 23% among non beneficiaries than among the beneficiaries of RTEP. Net yield per hectare increased by a range of about 13.00 to 18.52 metric tons while net crop income per hectare increased by a range of about ₦39,705 to ₦42,133 ($198-211) thus, reducing poverty by about 5 to 20%. The factors that positively influenced the probability of adoption of RTEP were: years of education, social capital, farm size and access to improved planting materials while planting of two or three root crops negatively influenced the probability of adoption of RTEP. Therefore, policy options that favor increased education, farmer group membership and access to improved inputs are recommended to encourage RTEP adoption and further reduce poverty among farmers.

Key words: Root and tuber crops, beneficiaries, poverty, adoption, logit.

INTRODUCTION

Poverty reduction and elimination remain key issues of development globally. Poverty has traditionally been higher in rural areas than urban areas despite the bulk of agricultural activities that take place in rural areas. In sub-Saharan Africa (SSA), a greater proportion of the population resides in rural areas and the poverty rate stands at about 50% (Anyawu, 2012). Agriculture remains the mainstay of most economies in the region accounting for a vast majority of the working population. Paradoxically, agriculture has been the locus of poverty in SSA countries, especially in Nigeria which has the highest population of poor people in the region. About 70% of Nigeria‟s 160 million population is poor and about 60% of the people are engaged in agriculture (NBS, 2012). The welfare of farmers remain generally low due to declining productivity which could be attributed to low technical know-how on crops (that is, agricultural technology) to improve income and food security (Amao and Awoyemi, 2008). Agricultural technology contributes to poverty reduction In terms of enhanced productivity

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and lower per unit cost of production which raise income of adopting farmers (Menale et al., 2011). It follows that the lack of agricultural technology not only results in decreasing capacity to meet the food needs of the people, but also creates critical limiting factors to all-year-round cultivation given that production in SSA countries is largely weather-dependent. Hence, research and adoption of crops having the ability to withstand drought, diseases, improved yield and be cultivated throughout the year is crucial for food security and poverty reduction in the region.

Root and tuber crops rank high as drought resistant crops grown all-year-round hence, have become important staple foods consumed in SSA, accounting for about 20% of calories consumed in the region (Scott et al., 2000). For instance, annual mean per capita consumption of cassava in Africa is about 140 kg (Philips, 1998). In Africa‟s most populous country, Nigeria, root and tuber crops are the second most important food crops, after cereals and they have the potential to contribute significantly to food security (Kays and Paull, 2004). They are used to alleviate seasonal shortages and fill food gaps caused by natural or man-made disasters (Tanganik et al., 1999). The crops also serve as raw materials in manufactured products for both rural and urban consumption in addition to providing income sources for resource poor farming households (Nwakor et al., 2011). Given the global drive towards poverty reduction and welfare maximization, root and tuber crops have become increasingly important for household and social welfare among rural dwellers.

Government intervention in the development of root and tuber crops as major food crops in Nigeria has been high due to their food security role, drought resistant capability and their potential for commercial processing. Since the 1980s, government efforts have generally focused on development of high yielding varieties that are tolerant to pests and diseases. Various interventions aimed at improving sustainable productivity, farmers‟ income and the quality of lives of rural households have also been instituted. Cassava has been most favored among the roots and tuber crops for government interventions in Nigeria which include: The Cassava Multiplication Program (CMP) which took off in 1989, the Root and Tuber Expansion Program (RTEP); launched in 2000 and the Presidential Initiative on Cassava (PIC); formed in 2002.

The CMP and the PIC mainly focused on improving production and have helped to boost Nigeria‟s cassava production, making the country the largest cassava producer in the world (FAO, 2013). In addition, the programs facilitated the building of domestic productive capacity to efficiently, profitably and sustainably satisfy the market demand with the quality and quantity required (PIC, 2003). The RTEP, on the other hand, was tailored to address the welfare of the farmers in addition to increased production.

The root and tuber expansion program (RTEP)

The root and tuber expansion program (RTEP) was formulated to address issues of food production and rural poverty (RTEP, 2010). At the local farmers‟ level, the program aims to achieve economic growth, improve access of the poor to social services and carry out intervention measures to protect poor and vulnerable groups. At the national level, the program was designed to achieve food security and stimulate demand for cheaper staple food such as cassava, yam, cocoyam, potato etc. (Adeniyi, 2009). Commercialization of roots and tuber production, improving the living conditions, income, food security and nutritional health of poor smallholder households in the program area were the main objectives of RTEP. The overall target group was about 5.2 million small holders with less than 2 to 3 ha of land holding per household in Nigeria (PIM 2001 in Ibrahim and Onuk, 2010). However, due the introduction of the Presidential Initiative on Casava Program, most farmers including the RTEP farmers, took advantage to expand their farm sizes because of the commercialization benefit of the program. Improved technology for storage of fresh cassava cuttings during the dry season and seed yam production through yam mini sett technology to increase production were also provided to the programme beneficiaries. In addition, actions strategies to strengthen downstream activities, check incidences of low prices in producing communities, bridge income disparities, and enhance employment were also incorporated into the programme.

Generally, increase in production of root and tuber crops with little income to the farmers has been observed in Nigeria, due to poor processing and marketing strategies. Ater et al., (2006) observed that the RTEP programme led to increased production and market glut in the 2006 farming season with consequent low prices in the producing communities which ultimately became a dis-incentive to producers. Cassava post-harvest losses continue to be significant, especially when seasonal surpluses are high. Population pressure on the land has also significantly reduced soil fertility in many parts of the country while fertilizers are expensive and frequently unavailable to the farmers (RTEP, 2010). These challenges have implications for the farmers‟ poverty status and welfare. Given the dismal picture of roots and tuber crops production in Nigeria, adoption of program such as RTEP may be vital to lifting farmers out of the poverty trap.

Many poor farmers are yet to participate in RTEP and they remain outside the program, not benefitting from its several advantages. The farmers‟ non involvement may be as a result of being unaware of the potential benefits of participating in the project (RTEP, 2010). Expanding the number of beneficiaries will invariably lead to the need for increased funding of the program. There is therefore a need for the assessment of the program to justify such funds. Further, an impact assessment will provide government and policy makers with facts for implementing and/or changing intervention strategies in order to achieve the program goal of reducing farmers‟ poverty levels. Past studies on RTEP impact assessment (Tijani and Thomas, 2010; Ibrahim and Onuk, 2010; Ater et al., 2006) have only assed the impact of the program on the beneficiaries using descriptive and inferential statistics which do not ensure that the factors isolated to affect RTEP technology adoption and poverty reduction are actually traceable to the program alone and no other source, hence, the evaluation problem arises which produces biased estimates. A more recent study by Obisesan and Omonona (2013) employed the propensity score matching (PSM) to address the evaluation problem and employed the counterfactual outcome framework to show the impact of the outcome defined in the modern policy evaluation literature as the average effect of the treatment on the treated (ATT) which helps to reduce biased estimates. However, the study assessed the impact of RTEP on the food security status of the farmers and not poverty reduction. Therefore, the study seeks to assess the impact of Root and Tuber Expansion Program (RTEP) on farmers‟ welfare and to find out the factors influencing adoption of the program in Southwest Nigeria.

THE COUNTERFACTUAL FRAMEWORK

Social programmes are appropriately assessed before and after an intervention to ascertain the nature of their outcomes. Impact assessment of the outcomes of a social program on a group of farmers must take into consideration the counterfactual (Angrist et al., 1996; Heckman, 1996; Heckman and Vytlacil, 2007a, 2007b; Rosenbaum and Rubin, 1983; Wooldridge, 2002; Dontsop-Nguezet, 2011). This is because observations are made on farmers who have and have not been exposed to the programme. Observing only exposed farmers will give rise to biases. Some farmers participate in the programme while others do not participate, but not both. Every farmer in the population thus has two *potential* outcomes: With and without adoption of the technology. Individual *i* can either participate or not participate in the programme, but not both, and thus only one of these two potential outcomes can be realized. A counterfactual framework allows us to examine all possible responses for each individual in the sample. For example, let the first potential outcome be $y_{i(0)}$; the outcome that would be realized by farmer *i* if he or she did not participate in the programme. Similarly, let the second potential outcome be $y_{i(1)}$; the outcome that would be realized by farmer *i* if he or she adopts the new technology. The outcome variables $y_{i(0)}$ and $y_{i(1)}$, are further separated into an average components, u_1 and u_0, and an individual-specific component, v_1 and v_0. Thus, we have:

$$y_{0i} = u_0 + v_0 \tag{1}$$

$$y_{1i} = u_1 + v_1 \tag{2}$$

Information about y_i provides us with evidence to establish an *associative relationship* between treatment and response. The difference between y_{1i} and y_{0i} ideally, gives the impact of treatment on each farmer such that we can infer a *causal relationship* based on the counterfactual (Neill and Lee, 2001). However, since a farmer is either treated or not treated, y_{1i} and y_{0i} are mutually exclusive and the counterfactual is therefore unobservable (Heckman and Vytlacil, 2001). The observed outcome y_i is a function of both potential outcomes and treatment status given as:

$$y_i = d_i \cdot y_{1i} + (1 - d_i) y_{0i} = y_{0i} + d_i (y_{1i} - y_{0i}) \tag{3}$$

Where d_i is the binary treatment variable that takes the value 1 with treatment and 0 in its absence.

The binary outcome variable in the absence of treatment, y_{0i} for all individuals equals zero since a new technology cannot be adopted without prior knowledge of it by the farmers. Thus, we can observe $y_{0i} = 0$ for the untreated farmers. On the other hand, y_{1i} remains unobservable for all farmers since we cannot observe the counterfactual corresponding to any technological, institutional or policy change being considered. This is because if the change does occur, one cannot observe what would have happened to the outcomes in the absence of the change. In the same way, if the change does not occur, one cannot observe what would have happened to the outcomes if the change did actually take place. This scenario is depicted in Figure 1.

A most robust evaluation of the impact of a social programme (or research solution) requires randomized experiments (Burtless, 1995). Randomized experiments create a control group of individuals with identical distributions of observable and unobservable characteristics to those in the treatment group (within sampling variation). The randomly determined adoption helps to overcome the selection problem. Hence, Imbens and Angrist (1994) introduced the concept of the compliance type of an individual which describes the level of the treatment that an individual would receive given each value of the instrument. This is captured by the pair of values (Wi(0), Wi(1)) where Wi is an outcome variable. This is a binary instrument with both the treatment and the instrument binary such that responses for potential treatment (Ti) takes any of four responses; *Never-taker* if $Wi(0) = 0$, $Wi(1) = 0$; *Complier* if $Wi(0) = 0$, $Wi(1) = 1$; *Defier* if $Wi(0) = 1$, $Wi(1) = 0$ and *Always-taker* if $Wi(0) = Wi(1) = 1$.

In separating the treatment effect of the treated and untreated farmers (W_i) on the outcome (y_i), we have to consider the other variables (x_i) such as socio-demographic (covariates) and the error term ε_i affecting y_i

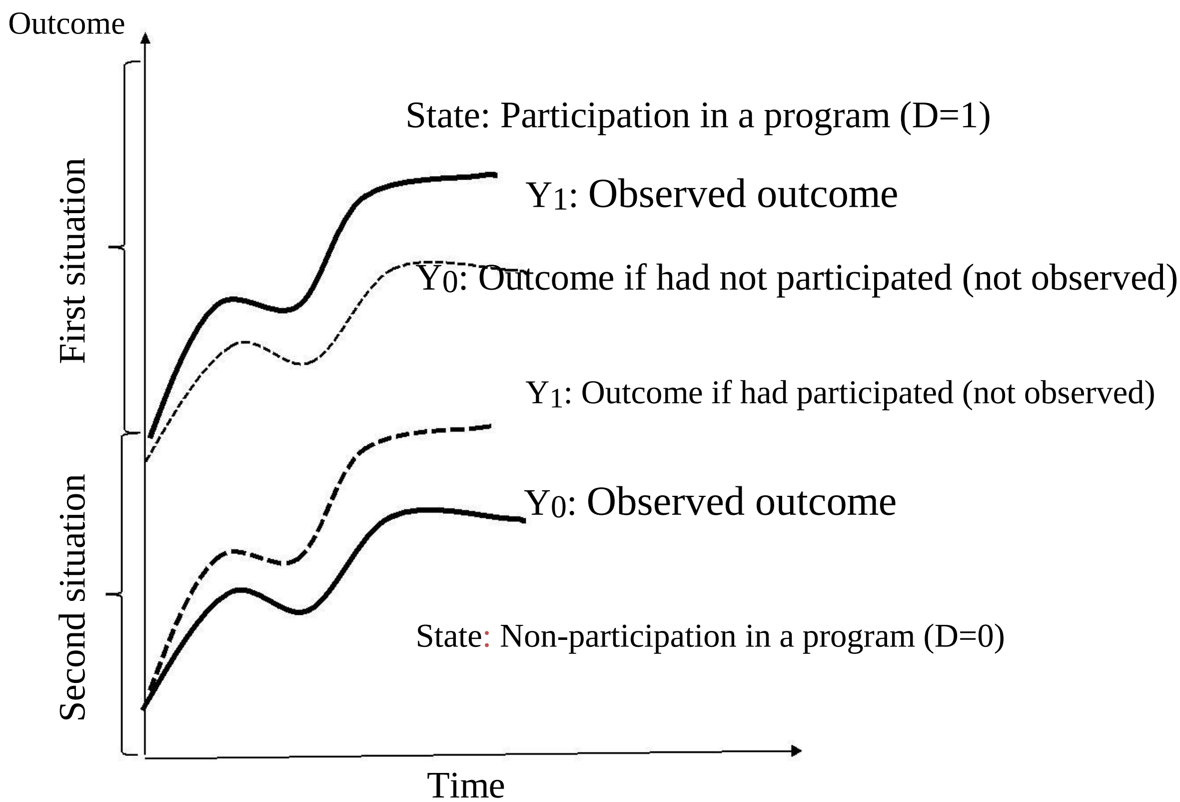

Figure 1. The fundamental evaluation problem: Observed and unobserved outcomes under *mutually exclusive* states.

and W*i*. In cross-section context as is used in this study, if x_i or ε_i differs across i, then it is not clear to what extent the differences in y_i across i are and if they are due to the differences in W_i across i. Hence, controlling for x_i and ε_i that are heterogeneous across i is the main task in treatment effect analysis with observational data (Dontsop-Nguezet, 2011) without which the problem biases will arise.

Two types of biases were identified by Rosenbaum (2002): Overt and hidden biases. If the Treatment group (T group) differs from the Control group (C group) in x, then the difference in x, not in W, can be the real cause for $E(y|W = 1) \neq E(y|W = 0)$; more generally, $E(y|W = 1) \neq E(y|W = 0)$ can be due to differences in both W and x; whenever the difference in x contributes to $E(y|W = 1) \neq E(y|W = 0)$, we incur an *overt bias*. On the other hand, if the T group differs from the C group in ε, then the difference in ε may contribute to $E(y|W = 1) \neq E(y|W = 0)$; in this case, we incur a *hidden (covert) bias*. In practice, however, bias estimates with randomized experiments occur if the implementation of the experiment itself alters the framework within which the programme operates, creating what is known as „randomisation bias" (Heckman et al., 1998). Randomisation bias occurs with the problems of programme dropouts and comparison group substitution. Programme dropouts are treated farmers who later opt out of the programme, not allowing for identification of treatment on the treated but rather the mean effect of „intent to treat". Comparison group substitution occurs when those denied treatment choose to participate in programmes that are effective substitutes for the programme under evaluation (Dontsop-Nguezet, 2011). Non-experimental methods can be used to correct these problems. The choice of the non-experimental method to use in any programme evaluation depends mainly on the characteristics of the programme and the nature and quality of available data. However, in non-experimental techniques, an observable counterfactual is absent, hence; assumptions have to be made to identify the causal effect of a policy or programme on the outcome of interest. These assumptions can be called „identifying assumptions". In general, the fewer assumptions you make, and the more plausible they are, the more likely it is that estimated effects will approximate real programme effects (Dontsop-Nguezet, 2011).

MATERIALS AND METHODS

Empirical estimation

The decision to be influenced to participate in RTEP or not can be explained as a discrete variable. Hence , regarding choice of

Table 1. Covariates and their expected signs for Probit model.

Variables	Expected sign
Age	+
Sex	-
Education	+
Number of years spent in root and tuber farming	+
Access to credit	+
Social capital	+
Farm size	+
Two crops planted	+
Three crops planted	-

models, the most important aspect of the decision framework is the dichotomous dependent variable. Classical linear methods are inappropriate for dichotomous choices since they can lead to heteroscedasticity variances. This problem is typically remedied by using maximum likelihood estimation (MLE), although heteroscedasticity in MLE is also a potentially serious problem leading to inconsistent estimators (Greene, 2000). According to Wooldridge (2000), when heteroscedasticity is observed, such models require more general estimation. However, such models are not often used in practice, since logit and probit models with flexible functional forms in the independent variables tend to work well. The probit model was used to determine the factors that influence the probability of adoption of RTEP while both probability models (logit and probit models) were used in the matching algorithm. The description of the variables specified in the probit model for the probability of adoption of RTEP and their expected signs are is given on Table 1.

In real life, groupings of farmers into adopters and non-adopters occur due to self-selection rather than randomized assignment. The farmers make the decision either to adopt the RTEP programme or not based on individualities, which may be related to the outcome of interest (poverty, or crop yield). These individualisms could include managerial skill, motivation, and average land fertility (Menale et al., 2011). The problem of self-selection can produce biased results if not accounted for. The Heckman and instrumental variable methods can be used to deal with the self-selection problem however, they impose distributional and functional form assumptions which could pose further problems in cross sectional data analysis. Hence, this study uses propensity score matching (PSM), a non-experimental statistical matching technique, to make the treated group of RTEP beneficiaries more comparable with the untreated group (non-beneficiaries) under non-random conditions of selection. Each adopter of RTEP (beneficiary) is matched with a non-adopter possessing similar characteristics. This creates the conditions of an experiment in which adopters and non-adopters are randomly assigned, allowing for the identification of a causal link between the choice to participate in RTEP and outcome variable (increase in income and poverty reduction). The PSM is widely used to assess the effect of social programmes since it provides counterfactual situation which reveals what would have occurred if the treated had remained without the intervention/project. The assumption that selection is based on observable variables is a drawback with the use of PSM because unobservable variables that may affect both the outcome variables and choice of technology are not accounted for directly.

PSM method requires that propensity scores, which are the probability of adoption for each observation, be first calculated. Following Menale et al., (2011), each adopter was matched with a non-adopter having similar propensity scores using nearest neighbor matching (NNM) and kernel-based matching (KBM) study after which the mean absolute standardized bias (MASB) balancing test was applied. The MASB was employed to ascertain whether the two groups in the matched sample had no differences in covariates. The MASB balancing test was first applied by Rosenbaum and Rubin (1983) in which a standardized difference of greater than 20% was considered too large and a failed matching process. Comparison of the pseudo-R^2 and p-values of the likelihood ratio test of the joint insignificance of all the regressors obtained from the probit and logit analysis before and after matching the samples also reveal the absence of systematic differences in the distribution of covariates between the two groups (Sianesi, 2004). Hence, the pseudo-R^2 after matching should be lower and the joint significance of covariates should be rejected while the p-values of the likelihood ratio should be insignificant.

Estimation of poverty measures

The Foster–Greer–Thorbecke (1984) indices commonly referred to as FGT, were used to measure poverty. The FGT poverty measure is given as:

$$FGT_\alpha = \frac{1}{N}\sum_{i=1}^{H}(\frac{z-y_i}{z})^\alpha$$

where *N* is the sample size, *z* is the poverty line, *y* is per capita income for the ith person, and α is the poverty aversion parameter. When α= 0, Pα is the headcount index or the proportion of people that is poor; when α = 1, Pα is the poverty gap index, a measure of the depth of poverty and when α = 2, Pα is a measure of severity of poverty and reveals the degree of inequality among the poor. The poverty line used in the study was two-thirds of mean per capita household expenditure (MPCHHE) in the study area.

Data collection

This study was carried out in Oyo State, which is one of the six states in South-West Nigeria. The state has 33 Local Government Areas (LGAs) and a population of 5,591,589 (NPC, 2006). The state capital, Ibadan, is the largest city in West Africa. The climatic condition of Oyo state is tropical and it favours the production of wide varieties of food crops including root and tuber crops such as cassava, yam, cocoyam and sweet-potato. Four (4) Agricultural Development Project (ADP) zones exist in the state as categorized by the Oyo state Agricultural Development Project (OYSADEP): Ibadan/Ibarapa zone, Oyo zone, Ogbomoso zone and Saki zone.

Table 2. Socio-economic characteristics of root and tuber crop farmers (n=161).

Variable	Beneficiaries	Non-beneficiaries	t-statistics
Gender			
Male (%)	80.8	75.0	
Female (%)	19.2	25.0	
Age (mean)	48.67	48.25	-0.26
Household size (mean)	6.88	6.91	0.09
Years of education (mean)	6.12	6.19	0.08
Years of farming experience (mean)	20.99	13.80	-3.87*
Farm size in *ha* (mean)	1.54	1.75	1.39
Output in *tones* (mean)	19.05	12.30	1.98**
Yield in *tones/ha* (mean)	12.72	7.03	-1.95**
Crop income *N/ha* (mean)	39,706.46	27,050.11	2.25**

*Significant at 1%, ** 5%, ***10%.

Hence, the major occupation of the people is farming (OYSADEP, 2010).

The data for the study was collected in 2010 through the use of structured questionnaires while employing a multistage sampling technique. Oyo state was selected at random from a list of six states in the Southwest zone of the country, which participated in the RTEP. The second stage involved the random selected of three out of four ADP zones (Ibadan/Ibarapa, Ogbomoso and Oyo zones). Next, one LGA was selected from each ADP zone (Ibarapa Central LGA from Ibadan/Ibarapa zone, Ogo-Oluwa LGA from Ogbomoso zone and Iseyin LGA from Oyo zone) and lastly, one village from each LGA. Root and tuber crop farmers were found in all villages but RTEP was not adopted by all the farmers, hence; both participating and non-participating farmers were randomly selected in each village. A total of 60 farmers were selected in each village to give a sample size of 180 farmers comprising both RTEP and non RTEP farmers. Only 161 questionnaires (73 beneficiaries and 88 non-beneficiaries) were used for the analyses due to missing data.

RESULTS AND DISCUSSION

Descriptive statistics

The description of the farmers" characteristics is presented on Table 2 and it reveals that both groups of beneficiaries and non-beneficiaries have similar characteristics with only slight differences recorded. Root and tuber crop farming was a male dominated activity in the study area. Generally, male household heads were more than female household heads and there were more female household heads that were outside the RTEP than those participating in the programme. Most farmers were middle aged, still economically active and productive with mean age of about forty eight years. This agrees with Amaza et al., (2007) and makes them more inclined to adopting technology than older farmers, although their rate of adoption may not be as fast as younger farmers (Nwakor et al., 2011). Household size was fairly large with a mean of about seven persons per farming household. This closely follows Balogun and Obi-Egbedi (2012) finding of an average of six persons per household in South west Nigeria. The large household size has implication for the poverty status of the farmer. There was also an appreciable level of literacy among the farmers who had attained about six years of schooling. This is expected to have a positive effect on adoption of the programme.

With respect to the farm characteristics of farmers, RETP farmers had significant years of experience than the non RTEP farmers. Although the farmers did not differ significantly in terms of farm sizes, there were however significant differences in output, yield and crop income. This may be as a result of the cultivation of improved variety by the RTEP beneficiaries. Table 2 shows that mean farm sizes were about 1.54 and 1.75 ha for RTEP and none RETP farmers respectively while yield and mean crop income for both groups were about 12.72 and 7.03 tonnes/ha and ₦39,706.46 and ₦27,050.11, respectively.

Table 3 compares the poverty indices (headcount, depth and severity) of RTEP farmers/beneficiaries and non-beneficiaries in the study area. The poverty indices were computed using the Foster-Greer-Thorbecke (FGT) poverty measure. Two-thirds of mean monthly household expenditure per capital was used as the poverty line. Household expenditure was used instead of the income because it was difficult to capture all the income sources of the farmers. The table shows that poverty incidence is very high in the study area and particularly higher for non-beneficiaries of RTEP than the beneficiaries (by about 23%); hence, RTEP beneficiaries were less poor than the non-beneficiaries. The indices of depth and severity of poverty, which were also higher among non-beneficiaries than the beneficiaries by 8 and 2% respectively, revealing a high degree of income shortfall below the poverty line and a high degree of inequality among the poor.

Table 3. Poverty measures by adopter‟s status.

Poverty indices	Beneficiaries	Non beneficiaries
Headcount	0.45	0.68
Depth	0.11	0.19
Severity	0.05	0.07
Poverty line using 2/3 of MPCMHHE in ₦	5666.59	5259.84

Source: Author‟s computation using FGT measures; MPCMHHE, mean per capita monthly household expenditure.

Empirical results

The probit estimates of the adoption propensity equation are shown on Table 4. The pseudo R^2 value of 0.25 correctly predicts 73.90% of RTEP beneficiaries and 76.09% non beneficiaries. Correct predictions were slightly higher for non beneficiaries than beneficiaries. The likelihood ratio test of the hypothesis that the coefficients of all the explanatory variables are zero, has a Chi-square value of 54.90 with 11 d.f., suggesting that the estimated model is highly significant. The results also show that several variables were statistically significant at 1% level in influencing farmers‟ adoption of RTEP. These include, years of education, social capital, farm size and access to improved planting materials which were positively associated with the probability of adoption of RTEP while planting of two or three crops negatively influenced the probability of adoption of RTEP. Thus a 1% increase in years of education may likely increase the probability of a farmer‟s adoption of RTEP by 0.03%. This implies a highly inelastic response of 0.22% when evaluated at the mean values of the independent variables.

Education and social capital (which refers to membership of farmer groups) can be proxies for access to information (Menale et al., 2011) which could aid awareness and adoption of the programme. Conversely, a 1% increase in planting two or three different types of root crops is likely to decrease the probability of adoption of RTEP by 0.24 and 0.55%, respectively with inelastic responses of 0.40 and 0.16%, respectively. Farmers who practice the cultivation of a variety of root and tuber crops may not be able to easily adopt modern agricultural technologies disseminated to RTEP farmers due to high level of multiple cropping. This implies that policy options should be directed at encouraging farmers in crops of most efficient production. This will lead to increased productivity and income with the ultimate goal of poverty reduction.

Following from the estimation of propensity scores for RTEP beneficiaries and non- beneficiaries, we assess the quality of the matching process using the common support condition (Appendix 1 for a table on matching). Based on the marching exercise on column 2 Table 4, it was found that among beneficiaries, the predicted propensity score ranges from 0.1300 to 0.9776, with a mean of 0.6176, while among non-beneficiaries, it ranges from 0.0332 to 0.8499, with a mean of 0.3612. Thus, the common support assumption is satisfied in the region of [0.0332, 0.9776], with only a loss of 9 (5.6%) observations from beneficiaries. Figure 1 gives the histogram of the estimated propensity scores for beneficiaries and non-beneficiaries. A visual inspection of density distributions of the estimated propensity scores for the two groups indicates that there exist a substantial overlap in the density distribution of the estimated propensity scores of both beneficiaries and non beneficiaries; thus, satisfying the common support condition. This is shown in the intersection region of the common support graph shown on Figure 2. The bottom half of the graph shows the propensity scores distribution for the non-beneficiaries and the upper half refers to the beneficiaries. The density scores are on the horizontal axis.

A major objective of the propensity score estimation is to balance the distribution of relevant variables between the beneficiaries and non-non-beneficiaries, rather than obtain a precise prediction of selection into treatment. The kernel-based matching (KBM) and the nearest neighbor matching (NNM) were thus used to buttress the probit estimate results used to determine the factors influencing RTEP adoption. The basic approach is to numerically search for “neighbors” of non-beneficiaries that have a propensity score that is very close to the propensity score of the beneficiaries. The balancing test was afterward applied to ascertain whether the differences in the covariates of the two groups in the matched sample have been eliminated, in which case, the matched comparison group can be considered a plausible counterfactual (Ali and Abdulai, 2010). Table 5 shows the results from the covariate balancing tests both before and after matching. The standardized mean difference of about 18% (before matching) decreased to about 4 to 9% after matching. Consequently, the matching process decreased total bias by a range of about 49 to 80%.

The likelihood ratio tests showed that *p*-values before matching were all significant at 1% level indicating that the joint significance of covariates were accepted. However, after matching, the joint significance of

Table 4. Probit estimates of the propensity to participate in RTEP.

Variables	Coefficients (Std. error)	Marginal effects[a] coefficients	Elasticities coefficients
Age	-0.011(0.014)	-0.003	-0.222
Sex	0.189(0.319)	0.056	0.137
Years of education	0.113(0.044)*	0.033	0.219
Years of farming experience	0.023(0.025)	0.007	0.158
Access to credit	-0.093(0.288)	-0.027	0.054
Social capital	1.430(0.351)*	0.428	0.887
Farm size	0.219(0.078)*	0.065	0.738
Household size	0.047(0.055)	0.014	0.317
Accimpvl	0.701(0.238)*	0.206	0.271
Dumy2crp	-0.812(0.263)*	-0.239	-0.395
Dumy3crp	-1.859(0.617)*	-0.547	-0.164
Constant	-2.630(0.731)*		
Summary statistics			
Pseudo R^2	0.25		
Model chi-square	54.90*		
Log likelihood ratio	-83.45		
Non-adopters correctly predicted	76.09		
Adopters correctly predicted	73.90		
Number of observations	161		

Source: Authors" calculations. [a]Marginal effects evaluated at the sample means. [b]Accimpvl- Access to improved planting materials. *Significant at 1% (P < 0.01).

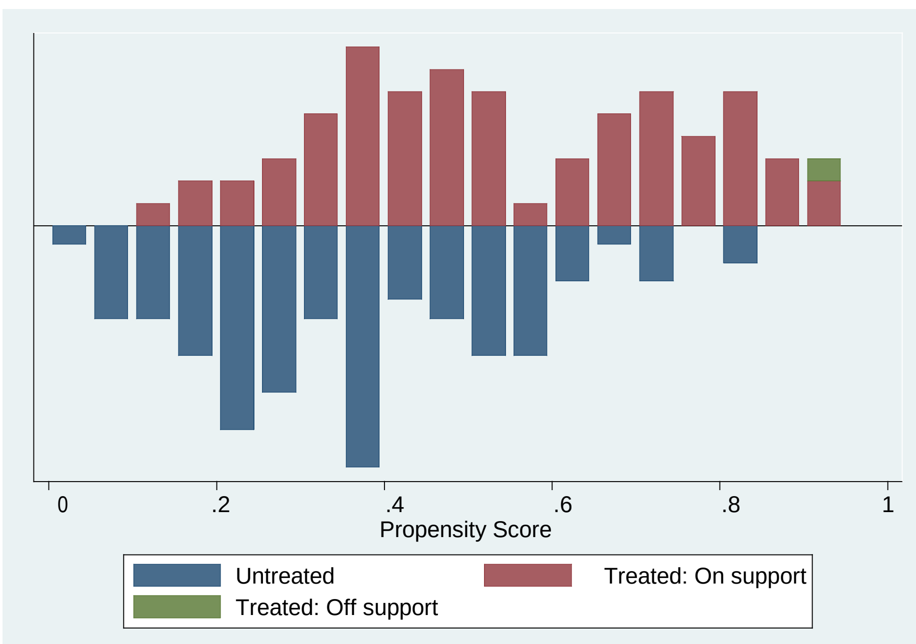

Figure 2. Propensity score distribution and common support for propensity score estimation. Treated: On support indicates the observations in the adoption group which have a suitable comparison. Treated: Off support indicates the observations in the adoption group which do not have a suitable comparison.

covariates was rejected due to their insignificance. Similarly, the pseudo-R^2 reduced from about 25% before matching to a range of about 0.03 to 0.09% after matching. As noted earlier, the outcome of the indicators

Table 5. Matching quality indicators before and after matching.

Matching algorithm	Model type	Pseudo R^2 before matching	Pseudo R^2 after matching	LR X^2 (p – value) before matching	LR X^2 (p - value) after matching	Mean standardized bias before matching	Mean standardized bias after matching	Total % |bias| reduction
NNM[a]	Logit	0.248	0.09	54.29 (p=000)*	7.55 (p=0.893)	18.397	9.439	48.7
	Probit	0.248	0.04	54.29 (p=000)*	8.47 (p=0.671)	18.397	7.816	57.5
NNM[b]	Logit	0.248	0.035	54.29 (p=000)*	6.88 (p=0.809)	18.397	4.259	76.8
	Probit	0.248	0.025	54.29 (p=000)*	4.84 (p=0.938)	18.397	4.906	73.3
KBM[c]	Logit	0.248	0.026	54.29 (p=000)*	4.19 (p=0.964)	18.397	4.909	73.3
	Probit	0.248	0.033	54.29 (p=000)*	5.43 (p=0.909)	18.397	4.235	80.0
KBM[c]	Logit	0.248	0.035	54.29 (p=000)*	6.75 (p=0.819)	18.397	6.519	64.6
	Probit	0.248	0.04	54.29 (p=000)*	7.73 (p=0.737)	18.397	7.286	60.4

[a]NNM = single nearest neighbor matching with replacement and common support. [b]NNM = five nearest neighbors matching with replacement and common support. [c]KBM = kernel based matching with band width 0.03 and common support. [d]KBM = kernel based matching with band width 0.06 and common support. *Significant at 1%.

Table 6. Impact of adoption on all crop income and poverty status and Rosenbaum sensitivity analysis results.

Matching algorithm	Outcome	ATT		Critical level of hidden bias	
		Logit	Probit	Logit	Probit
NNM[a]	Yield per hectare (in „000 tones)	15.83 (3.25)*	12.98 (-2.96)*	4.6	4.2
	Net crop income per Hectare (in „000	40.734 (3.31)*	40.447(3.02)*	4.5	4.3
	Poverty (headcount ratio)	-0.098 (-0.49)	-0.052 (-0.25)	1.0	1.2
NNM[b]	Yield per hectare (in „000 tones)	14.14 (1.91)***	14,073 (3.07)*	3.0	3.0
	Net crop income per Hectare (in „000₦)	39.705 (1.96)**	40.447 (3.13)*	3.1	3.1
	Poverty (headcount ratio)	-0.069 (-0.21)	-0.1089 (-0.27)	1.3	1.3
KBM[c]	Yield per hectare (in „000 tones)	18.52 (2.02)**	14,545 (2.08)**	3.8	3.6
	Net crop income per Hectare (in „000₦)	40.734 (1.85)***	42.133 (2.13)**	4.0	3.9
	Poverty (headcount ratio)	-0.061 (-0.19)	-0.199 (-0.67)	1.3	1.6
KBM[d]	Yield per hectare (in „000 tones)	15,991(1.79)***	16,822(1.80)***	3.9	4.4
	Net crop income per Hectare (in „000₦)	40.447 (1.83)***	41.010 (1.98)**	4.1	4.3
	Poverty (headcount ratio)	-0.029 (-0.09)	-0.062 (-0.20)	1.5	1.4

[a]NNM = single nearest neighbor matching with replacement and common support. [b]NNM = five nearest neighbors matching with replacement and common support. [c]KBM = kernel based matching with band width 0.03 and common support. [d]KBM = kernel based matching with band width 0.06 and common support. *Significant at 1%. **Significant at 5%. ***Significant at 10%.

show that the proposed specification of the propensity score has a balanced distribution of covariates between the RTEP beneficiaries group and non beneficiaries.

Table 6 reports the estimates of average adoption effects estimated by NNM and KBM. Although the results from the logit and probit models show different quantities in terms of value, the findings are similar in quality and direction. Hence, the results show that adoption of RTEP significantly increases yield, crop income and reduces poverty. Net yield per hectare increased by a range of about 13.00 to 18.52 metric tons while net crop income per hectare increased by a range of about ₦39,705 to 42,133 thus, reducing poverty by about 5-20%. The findings are consistent with past studies on the impact of agricultural technology on household welfare (Mendola, 2007; Dontsop-Nguezet et al., 2010; Menale et al., 2011). The Rosenbaum sensitivity analysis results also shown on Table 6 reveal that the critical level of hidden bias ranged from *T* = 1.0-4.6; where *T* is the critical value at which point we would question our conclusion of a positive effect of adoption of RTEP on yield and crop income and a negative effect on poverty status. It implies that if individuals with the same covariates differ in their odds of adoption by a factor of 50 to 70%, the significance of the adoption effect on the outcome variables may be questionable.

CONCLUSION AND RECOMMENDATIONS

The study has assessed the impact of the Root and Tuber Expansion Program (RTEP) on crop income and poverty reduction in rural Southwest Nigeria. The propensity score matching technique was used to estimate the benefits of participating in RTEP. The technique employed eliminated selection bias on observable differences between beneficiaries and non-beneficiaries of RTEP although some unobservable variables might correlate with adoption in addition to yield, crop income and poverty. The results of the empirical estimation showed that adoption of RTEP significantly increases yield, crop income and reduces poverty of the farming households. Adoption of RTEP increased yield and crop income by a range of about 13.00 to 18.52 metric tons and ₦39,705 to ₦42,133 respectively and reduced poverty by a range of about 5 to 20%. Furthermore, the factors that positively influenced the probability of adoption of RTEP were: years of education, social capital, farm size and access to improved planting materials while planting of two or three root crops negatively influenced the probability of adoption of RTEP. The findings of this paper showed that there is a lot of room for RTEP to achieve its poverty reduction goal among its adopters by going beyond merely increasing farmers‟ income to significantly reducing poverty among them. Therefore, the study recommends that concerted efforts be made to: improve the education of farmers beyond the basic level, discourage multiple cropping, increase the presence of ADPs in the rural areas and increase enlightenment for membership of farmers groups in order for farmers to escape poverty.

Conflict of Interest

The authors have not declared any conflict of interest.

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APPENDIX

Appendix Table 1. Matching of respondents‟ of covariates.

Variable	Unmatched/matched	Treated	Control	% Bias	% Reduction in bias	t-values	p-values
Age	Unmatched	19.648	20.721	-6.3	-4.1	-0.40	0.691
	Matched	19.514	18.398	6.6		0.44	0.662
Sex	Unmatched	0.82192	0.75	17.5	44.4	1.10	0.274
	Matched	0.81429	0.77429	9.7		0.58	0.562
Years of education	Unmatched	3.3471	2.0419	37.1	64.8	2.39	0.018
	Matched	3.3191	2.8602	13.0		0.72	0.475
Years of farming experience	Unmatched	6.4585	6.8544	-4.7	-174.1	-0.29	0.770
	Matched	6.1372	5.0522	13.0		1.05	0.297
Access to credit	Unmatched	0.75342	0.625	27.8	73.3	1.75	0.082