



Small-scale Farming, Agricultural Productivity and Poverty Reduction in Nigeria: The Enabling Role of Agricultural Technology Adoption

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Authors' contributions

This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.

Article Information

DOI: 10.9734/JAERI/2019/v19i130074

Editor(s):

(1) Dr. N. Karunakaran, Department of Economics and Vice-Principal, EK Nayanar Memorial Govt. College, Elerithattu, India.

Reviewers:

(1) Edward Tsinigo, Ghana.

(2) Msafiri Y. Mkonda, Sokoine University of Agriculture, Tanzania.

Complete Peer review History: <http://www.sdiarticle3.com/review-history/34328>

Original Research Article

Received 01 November 2017

Accepted 11 January 2018

Published 02 July 2019

ABSTRACT

Existing literature affirms the importance of agricultural technology adoption on productivity, income and livelihood outcomes. Evidences subsist on the adoption of improved cassava varieties (ICVs) in Nigeria but little is known about its impact among the farmers. We used data from a survey conducted by International Institute of Tropical Agriculture (IITA) to explore this research gap. Propensity Score Matching and Heckman's two-stage model were the analytical tools. Given an estimated poverty line of (₦21717.53); 52.0% of the farmers were poor. We found that 75.6% of the respondents are adopters of ICVs. Primary occupation of household head and total non-production asset of farmers were key determinants for adoption. Adoption of improved cassava variety has positive effect on farmers' productivity and poverty reduction. The Average Treatment Effect on the Treated (ATT) for productivity increased by 70 percent among ICVs farmers. Income was also higher among the adopters than the non-adopters by ₦43463.77. In the same vein, the

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income of the adopters increased by 17%. Furthermore, adopters of ICVs have the probability of reducing poverty headcount by 20%. The empirical results suggest that improved agricultural innovation adoption can play a key role in strengthening and impacting agricultural productivity of smallholder farmers for increased income generation and food security.

Keywords: Adoption; productivity; Nigeria.

JEL Classification: B21, I32, Q18.

1. INTRODUCTION

In Nigeria, agriculture is the source of food for the populace as well as raw materials for the agro-industries and contributes about 33% to the Gross Domestic Product of the nation (Bureau of African Affairs, 2010). The sector employs about one-third of the total labor force and provide a livelihood for the bulk of the rural populace (FMARD, 2006). Nigeria is an agrarian society with about 70% of her population (approximately 140 million) participating in agricultural production [1].

For many decades, notable international organizations such as International Institute of Tropical Agriculture (IITA) and International Rice Research Institute (IRRI) have collaborated with national research institutes under various programs, with financial supports from different quarters to device means through which cassava production can be improved sustainably. Among the different strategies, the development of high yielding improved cassava varieties is the most important and widely publicized. This is due to the green revolution experience in Asia, whereby the productivity of major staple food crops increased tremendously due to adoption and diffusion of the improved agricultural technologies. Hence, it is believed that the adoption of improved cassava planting materials will also produce a Nigerian Green Revolution with a view of fostering agricultural productivity with positive implication on national and household food security.

In order to combat the virulent cassava bacterial blight disease ravaging cassava in Nigeria, the National Root Crops Research Institute, Umudike, shortly after 1976 released some resistant and high yielding cassava varieties as follows: -NR 41044, NR 8082, NR 8083, NR 8212, NR 8267 and NR 8233 etc. In a bid to reduce the fear of cyanide poison pre-empted by cassava consumers, IITA in/ badan, developed some high yielding and low cyanide cassava varieties notably - TMS 4(2)1425, TMS 30001.

The National Root Crops Research Institute, Umudike, in the late 1980 also released five low cyanide cassava varieties (Sweet cassava varieties) namely: NR 84175, NR 84292, NR 84104, NR 8959 and NR 8421 (Eke-okoro and Njoku, 2012).

The low level of productivity of major staple food crops coupled with the high rate of poverty in most developing countries has become a problem that needs urgent attention. Thus, many developing countries have developed agricultural policies and programs that centered on increasing agricultural productivity and poverty reduction. Several studies has revealed that Nigeria's poverty incidence stood at 54.4%, implying that approximately 69 million Nigerians lived in poverty, this increased to 69% (or 112.5 million Nigerians) in 2010 (Nigeria Bureau of Statistics {NBS}, 2012). Specifically, poverty in the southwestern geopolitical zone rose to 59.1% in 2010 from 43% in 2004, implying that about 16.5 million people live in poverty (NBS, 2012). It therefore becomes pertinent to address agricultural policies and programme capable of tightening the inequality gap. Ironically, the number of poor population continually increases with rising growth in Nigeria (Oseni 2012; NBS, 2012).

On the overall, improved agriculture technologies adoption is now recognized as a one of the necessary conditions in the attainment of increase agricultural productivity, attainment of food security and overall poverty reduction ravaging many developing countries. Despite the numerous improved cassava varieties that have been released and, adopted by the farmers coupled with the fact that the new varieties have been reported to have a higher yield of about 16 tones/ha compared with the traditional varieties with only 10 tones/ha (Abdoulaye et al. 2014), the productivity of cassava is expected to have increased over the years, with a spillover poverty reduction effect among the rural smallholder cassava farmers.

Therefore, the pertinent research questions that need to be answered are:

1. How do socio-economic and demographic characteristics of the farmers influence adoption of improved cassava varieties in the study area?
2. How does the computed poverty indices for the adopters lower than the non-adopter of improved cassava varieties?
3. What is the impact of adoption of improved cassava varieties on productivity and poverty reduction?

Therefore, in order to provide answers to the above questions, this study carried out an empirical assessment of the impact of improved cassava varieties adoption on productivity and poverty reduction among the cassava-based farming households in two (Oyo and Osun) dominant cassava producing States in Nigeria. Specifically, we estimated and compare the poverty indices among the adopters and non-adopters of improved cassava varieties in the study area and empirically determine the impact of adoption of improved cassava varieties on productivity and reduction of poverty among the rural farmers in the study area.

This study is necessary in view of the fact that for many decades, Nigerian farmers relied solely on the local varieties and this dependence generated a great concern, particularly as it affects productivity. The limitations of the traditional varieties included low yield, long maturity period of up to three years and high tendency to be attacked by diseases such as Cassava Mosaic Disease (CMD) and brown streak disease (CBSD). Achieving a substantial increase in cassava yield which was one of the major goals of successive Nigerian governments and international organizations such as IITA over several decades require ability to overcome the above limitations (Awotide et al. 2014).

A decisive step towards overcoming the aforementioned limitations started in Nigeria when the Federal government initiated modern research into cassava in 1954. These research efforts led to the release of the first two IITA clones in 1976, these are; TMS 30395 TMS 30211 and which were immediately followed by TMS 30572, TMS 30001, TMS 30017, TMS 30110, TMS 30337, TMS 30555, TMS 4(2) 1425 and others in IITA 1984. This great achievement and breakthrough led to the continual increase of more efforts to improve cassava. The IITA

working with several partners have developed more than forty Improved Cassava Varieties in the last forty five years (Eke-Okoro and Njoku, 2012).

These improved varieties have been disseminated to the farmers and high rate of adoption has been recorded (Awotide et al., 2014). However, empirical information concerning the impact of the adoption of these improved varieties is still very limited. Many past studies on improved cassava varieties have centered on the intensity of adoption or the determinants of adoption using Tobit, Logit or Probit. Although assessing the intensity and determinants of the adoption of these improved varieties are also of great policy relevant. However, it is paramount that we have cogent and reliable empirical information on how much impact they have on productivity and poverty reduction. This suggests that a gap still exists in the literature that needs to be filled. Furthermore, in deviation from other studies, we intend to assess the impact rather than the effects of adoption on poverty by adoption model of impact assessment such as Propensity Score Matching (PSM) and Heckman two-stage model that have causal interpretation.

2. MATERIALS AND METHOD

2.1 Measurement of Poverty

This study adopted the income approach to poverty. Our primary measure of poverty is the cassava farmers' total household income. Our starting point in the measurement of poverty is the derivation of the threshold known as the poverty line, below which a cassava farming household can be adjudged to be poor. In the absence of a national poverty line, coupled with the fact that the use of absolute poverty line of \$1dollar in a day does not fit this kind of study, therefore, following Omonona [2]; Ruben and Van den Berg, 2001; Adewumi et al., 2011; Oyekale et al. [3], and Igbalajobi et al. [4], we calculated a relative poverty line, defined as two-thirds of the mean per capita total household income.

Several measurements of poverty have been developed and are used in the literature (Sen, 1976; Foster [5]; Foster-Greer-Thorbecke (FGT), 1984; Foster and Shorrocks, 1988). Observably, the FGT (1984), often called the p-alpha (P_α) class of poverty measure, is the most popular because the α is a policy parameter that can be varied to approximately reflect the poverty

“aversion” and also the P_α class of poverty indices is subgroup decomposable. Hence, this paper used the standard FGT (1984) to generate the poverty profile of the selected cassava farming households. FGT takes the form:

$$P_\alpha(y, z) = \frac{1}{N} \sum_{i=1}^n \left(\frac{Z - Y_i}{Z} \right)^\alpha \quad (1)$$

where,

- Z = the relative asset poverty line
- N = number of the cassava farmers below the poverty line
- N = Total number of cassava farmers sampled
- Y_i = estimated per capita household income of the i^{th} household
- $Z - Y_i$ = poverty gap of the i^{th} household
- $\frac{Z - Y_i}{Z}$ = poverty gap ratio
- α = poverty aversion parameter, with values: 0, 1, 2
- $\alpha = 0$, equation (1) gives the poverty headcount
- $\alpha = 1$, equation (1) gives the poverty depth
- $\alpha = 2$, equation (1) gives the poverty severity index

2.2 Impact of Adoption of ICVs on Productivity and Poverty Status of Adopters

Investigating the impact of adoption of improved varieties of cassava (ICVs) on poverty status of the adopters, a multivariate analysis was conducted. In order to extract the impact of ICVs from other interfering factors, counterfactual outcome is required and has to be established, this is to avert selection bias. As stated by Heckman and Smith (1999), the establishment of a counterfactual outcome represents the status of the farmers if ICVs were not introduced to the farmers. Zaini (2000) confirmed that these problems become more complex when participants self select into the project. A control group was used due to the difficulty in setting up a counterfactual situation. The control group was made up of non-adopters of ICVs. To allow for selection bias in the assessment of the poverty impact of ICVs adoption, the identification variable approach following the Heckman two-stage procedure was adopted to analyze the data. The unobservable factor which may create

bias in the outcome on poverty due to adoption of ICVs is referred to as ‘selection bias’. An appropriate and acceptable identification variable for this two-step procedure needs to be identified for the analysis. The identified variable needs to influence adoption but not poverty. Again if an acceptable identification variable was found, the results from the procedure can be sensitive to the choice of this variable. Because of this limitation the results from the analysis have to be checked for ‘robustness’ (Zaman, 2000).

This study adopted the ‘contact with extension agents’ and ‘relationship with institution through technology evaluation’ as the identification variable that affects adoption but not poverty. The choice of these variables was because of the fact that an increase in access to extension agents and relationship with institutions that bring innovation about the ICVs increases farmers’ knowledge about the ICVs and helps farmers make informed decisions on adoption. The impact of access to extension agents on poverty will depend not only on the number of ICV programmes taught but the quality of information and how convincing the programme is. In order to verify the choice of this identification variable its impact was tested on the adoption and poverty models.

Two stages are involved in the Heckman procedure, first is the estimation of the adoption process and second is the estimation of the poverty outcome. Going by the method of Zaman (2000), the adoption equation (first stage of Heckman model) estimates is;

$$D_i^* = \sigma + \delta X_i + \mu_i \quad (2)$$

D_i^* is a hidden variable representing the propensity of a farm household i to adopt ICVs, X_i is the vector of farm households’ asset endowments, household characteristics and location variable that influence the adoption decision.

Prior to the analysis, pair-wise correlation was conducted for the variables in the model and it was found that some of the variables were highly correlated. One of each pair of the highly correlated variables was dropped.

Using the maximum likelihood estimation procedure, the probability of adoption is derived from the first stage of the Heckman two-step technique. This involves employing a probit regression to predict the probability of adoption.

With these estimates, a variable which is known as the Mills ratio is obtained as follows:

$$C_i = \frac{\phi(\rho + \delta X_i)}{\varphi(\rho + \delta X_i)}$$

Where φ is the density function of a standard normal variable, ϕ is the cumulative distribution function of a standard normal distribution and C_i is the Mills ratio term. The addition of the Mills ratio to the poverty equation is the second stage. The factors that determine the extent of poverty are explained in details in the literature and these include the household and community characteristics. Lack of household ownership and access to assets that can be put to productive use are important determinants of poverty (Ellis and Mdoe, 2003; World Bank, 2000). The specific factors identified in the literature that determine poverty include demography or human factors (e.g. household size, age and gender, education and health) and social capital (membership in mutual support organizations); physical capital (ownership of livestock and other productive assets); community factors (access to infrastructure and services, population density, urban-rural or regional location; and external factors (civil strife, climate) (Benin and Mugarura, 1999).

The Heckman two-step model² is specified as follows; the first step (selection equation) of deciding whether farmer adopt or planted ICVs or not is empirically specified as:

$$\begin{aligned} \text{Adoption} = & \alpha_0 + \alpha_1 \text{ extensioncontact} + \alpha_2 \text{ instituterel} + \alpha_3 \text{ hhszise} + \alpha_4 \text{ lognonprodcasset} + \\ & \alpha_5 \text{ occup} + \alpha_6 \text{ age} + \alpha_7 \text{ eduys} + \alpha_8 \text{ tnonfarmincc} + \alpha_9 \text{ gender2} + \alpha_{10} \text{ land1ac} + \alpha_{11} \text{ logprodasset} + \\ & \alpha_{12} \text{ rentedland} + \alpha_{13} \text{ totalcosthlabour} + \alpha_{14} \text{ owntelevision} + \alpha_{15} \text{ ownmobile} + \alpha_{16} \text{ creditaccess} + \alpha_{17} \text{ ownradio} + \varepsilon_i \end{aligned} \quad (3)$$

The second step (outcome equation), which assesses the effect of market participation on the welfare of households (consumption expenditure per capita), is estimated empirically using OLS as follows:

$$\begin{aligned} \text{YIELD} = & \beta_0 + \beta_1 \text{ hhszise} + \beta_2 \text{ lognonprodcasset} + \beta_3 \text{ occup} + \beta_4 \text{ age} + \beta_5 \text{ eduys} + \beta_6 \text{ tnonfarmincc} + \beta_7 \text{ gender2} + \beta_8 \text{ land1ac} + \beta_9 \text{ logprodasset} + \\ & \beta_{10} \text{ rentedland} + \beta_{11} \text{ totalcosthlabour} + \beta_{12} \text{ owntelevision} + \beta_{13} \text{ ownmobile} + \beta_{14} \text{ creditaccess} + \beta_{15} \text{ ownradio} + \mu_i \end{aligned} \quad (4)$$

2.3 The Propensity Score Matching Technique

The PSM method was also adopted in this study, first to generate a group which can be used as control and then to tackle the problem of bias due to selection-on-observables (overt bias). The PSM method has been generally adopted in the impact evaluation literature for many years. Among many studies that have utilized the PSM in program impact evaluation include Cochrane and Rubin, [6], Rubin, 1973, 1979, Bassi, [7], Rosenbaum and Rubin [8], Friedlander et al., [9], Heckman et al., 1997, 1999; Heckman and Navarro-Lozano [10].

The PSM essentially estimates cassava farmer's propensity to adopt individually for any ICVs and it is commonly estimated using the Logit regression as a function of observable characteristics of the farmers and then matches each cassava farmer with similar propensities. The PSM produces a variable called the propensity score which is the probability that a farmer would adopt any ICVs which is based on the farmer's observable characteristics.

The propensity score (P(x)) is written as:

$$P(x) = \text{Pr}(T = 1 | X = x) \quad (5)$$

The obtained propensity score is usually used to create matched samples, uniform subgroups, and weight for balancing characteristics among the farmers and a variable for controlling or adjusting the data (Guo and Fraser, 2010). When farmers have similar scores (propensity), their assignment to the adopters is largely random with respect to relevant covariates, and thus takes the looks of a controlled experiment, thereby enabling us to accurately identify causal effects. The proficiency of the PSM is used to control for the variances in identified covariates that might influence the cassava farmers' adoption decision about ICVs is pivoted on the Conditional Independence Assumption (CIA)¹ which states that, conditional on observables characteristic of the cassava farmers (X), productivity and poverty reduction are independent of ICV adoption written as:

¹ See Wooldridge (2002)

$(TY_1, Y_0 \perp T | X)$. Another vital assumption is the common support or overlap condition: $0 < P(T = 1 | X) < 1$. According to Heckman et al. (1999), this condition ensures that the treatment observations have comparison observations “nearby” in the propensity score distribution. Only in areas of common support can inferences be made about causality. It is also very important to conduct a balancing test, that is, to ascertain if:

$$\hat{P}(X | T = 1) = \hat{P}(X | T = 0) \quad (6)$$

However, it is worthy of note that the estimation of the propensity score is a necessity but not sufficient condition to calculate the parameters of interest such as the Average Treatment Effect (ATE), Average Treatment Effect on the Treated (ATT), and Average Treatment Effect on the Untreated (ATU). There is a need to search for the fit counterfactual(s) that match individual adopter depending on its propensity score. The Nearest-Neighbour Matching (NNM) and the Kernel-Based Matching (KBM) approaches are the most commonly used matching methods. NNM pairs adopters and non-adopters with the same propensity scores, while the KBM measures treatment effects by subtracting from each outcome that is observed in the treatment group a weighted average of outcomes in the comparison group. The Average Treatment Effect on the Treated (ATT) which is the most important parameter to us in this study is then estimated by the average of the within-match differences in the outcome variable between the adopters and the non-adopters (see, for example, Dehejia and Wahba (1999), Rosenbaum (1995) and as follows:

$$\begin{aligned} E(Y_1 - Y_0 | T = 1) &= E[E(Y_1 - Y_0 | T = 1, P(x))] \\ &= E[E(Y_1 | T = 1, P(x)) - E(Y_0 | T = 0, P(x))] \end{aligned} \quad (7)$$

2.4 Data and Sampling Framework

The study was conducted in southwest Nigeria. The data for this study originated from a survey conducted by IITA in 2011. Among the six states that made up the Southwest geopolitical zone was chosen Fives states. But this study made use of data of two states out of the five states surveyed because they are the largest producers of cassava among the six states of southwest identified during the survey. These states are Osun and Oyo states. A three-stage stratified

random sampling procedure was used whereby states were used as strata to improve sampling efficiency and account for possible major differences in the adoption of improved cassava varieties across the states. The primary sampling unit was the Local Government Areas (LGAs) while Enumeration areas which are defined as a cluster of housing units were used as the secondary sampling units and households were the final sampling units.

Local Government Areas (LGAs) were selected from each state based on the probability proportional to size, where size is measured in terms of the number of Enumeration areas (EAs). The EAs that formed the sampling frame were obtained from the Nigerian Bureau of Statistics which uses the 2003/2004 master sampling frame of the National Integrated Survey of Households. The advantage of using the EAs as sampling unit is that each EA is approximately the same size. This ensured that all farmers had and equal probability of being selected. From each LGA, four EAs were selected at random from the sampling frame classified as rural or semi-urban, giving a total of 80 EAs. Finally, a list of households was formulated for selected EAs and sample of 10 farming households was chosen at random in each of the sampled EAs giving a total of at least 446 households. Questionnaires were administered at community and household level by trained enumerators with a senior agricultural economics in the field and the general supervision of IITA's economist.

The data that was gathered on the socio-economic characteristics of the respondents such as age of household head, marital status, sex, family size, level of formal education, reasons for farming, land acquisition method, years of farming experience, farm size (in ha) and on adoption. Input and output data such as cassava output, cost of input, income from output, labour output in man days were collected. The data collection was majorly on the socio-economic characteristics of the cassava farmers and cassava production variables.

3. RESULTS AND DISCUSSION

The distribution of the respondents by socio-economic characteristics is presented in Table 1. The result shows that representing 88% of the respondents were male. This suggests that cassava production is a male dominated venture and thus, it is expected that adoption of improved cassava varieties would be more prevalent

among the male headed households than the female counterparts. The distribution of the respondents by state shows that 46% of the respondents are from Osun State, while 54% are from Oyo State. The higher number of respondents from Oyo state is as result of the population size of the State.

Specifically in this study, farmers that have been planting improved cassava varieties for at least 5years consecutively are classified as adopters. This is to allow us to really identify real adopters of the innovation and hence, to be able to capture the impact on all the outcomes of interest more appropriately. Table 1 further reveals that 75.6% of the respondents are adopters, while 24.4% are non-adopters. It could be deduced that the improved cassava variety was well publicized by the extension agents in the two selected States, thus creating awareness and influencing the adoption rate. The primary occupation of the majority (89.4%) of the

respondents is farming. This shows that farming is the major occupation of the respondents. The percentage of farmers that have access to information is 76.5% while 23.5% have no access to information either through extension agent or other means. The high number of respondent that have access to information shows that information on new improved varieties of cassava is readily accessible through various channels to the farmers and this will have a positive effect on the adoption rate. In this study, household size is defined as the number of persons who usually reside in the same house, eat together from the same common pot and share the household expenditure. Going by this definition, people like parents, children and any other person who cooperate in the daily economic social life are referred to as household member. Analysis of the household size is a vital tool considered in this study as it determines the labor supply, production patterns and other household economic activities.

Table 1. Distribution of respondents by socio-economic characteristics

Socio-economic characteristics	Frequency (Total=446)	Percent (100)
Gender		
Male	393	88.1
Female	53	11.9
State		
Osun	207	46.4
Oyo	239	53.6
Adoption		
Non-adopters	109	24.4
Adopters	337	75.6
Primary Occupation		
Farming	397	89.4
Non-farm work	47	10.6
Access to information		
No access to credit	105	23.5
Access to credit	341	76.5
Household size		
0-5	317	71.1
6-10	124	27.8
11-15	5	1.1
Educational level		
Illiterate (no schooling)	170	38.1
Primary education	139	31.2
Secondary education	108	24.2
Tertiary education	29	6.5
Contact with extension agents		
No contact with extension agents	387	86.8
Contact with extension agents	59	13.2

Source: IITA/DIVA Adoption and Impact Survey (2011)

The household size distribution is also shown in Table 1. The result shows that most household have 0-5 members (71.8 percent) while next is 6-10 members with 27.8 percent and the least is 11-15 members having 1.12 percent. This findings depicts that majority of the farmers have small household size which could make the family labour supply to be limited, but on the contrary abates poverty because of increased per capita and general increment in well-being. Studies by World Bank (1999), Etim (2007) and Etim et al. (2008) reveal that a larger sized household is associated with greater poverty and vice versa. Considering human capital development, education happens to be a major tool and it's very effective at reducing poverty. It helps human to interact with his environment and it also determines the level of one understanding. It's an important tool for human skills development, knowledge and liberating people from poverty. The table further reveals that 38.1% of the respondents which makes a total of 170 do not have any formal education, while 31.2% had primary education, 24.2% had secondary education and 6.5% of the total respondents had tertiary education. Thus, it shows that majority of the farmers are literates and this could affect adoption of improved cassava varieties with a positive implication on productivity and income of the farming households. Information is strongly linked to awareness and without awareness adoption can never take place. Therefore farmers' contact with an extension agent is crucial to adoption of

improved agricultural technologies. The result displayed in Table 1 reveals that only 13.2% of the respondents had contact with the extension agent while 86.8% did not have contact with extension agents. Comparing the result of Table 3, 75.6% adopted the improved cassava variety but only 13.2% had contact with the extension agents. It can be deduced that there are other viable means through which farmers' access information on various improved practices other than contact with government extension agents. This conforms to findings of Omonona et al. (2006), Amao and Awoyemi (2008).

3.1 Characteristics of Adopters and Non-Adopters: Summary Statistics

The result of the test of mean difference in some selected socio-economic and demographic characteristics between the adopters and non-adopters is presented in Table 2. Result shows that on average, the adopters (54 years) were older than the non-adopters (51 years), although this difference is not statistically significant. It has been reported in the literature that older farmers are more experienced in farming than the younger ones and they are also risk takers than the young farmers. However, this is contrary to the findings of Ayoade (2013) which stated that age has negative impact on adoption of improved cassava.

Table 2. Mean difference in selected characteristics between adopters and non-adopters

Characteristics	Adopters (A) N=214	Non-adopters (NA) N=232	Mean difference	t- test	P- value
Age	53.95	50.95	3.00**	2.03	0.04
Years of education	5.39	5.38	0.01	0.03	0.98
Household size	4.55	4.74	0.19	0.99	0.32
Yield (kg)	2565.36	2413.77	151.59	0.48	0.63
Ave. Income/annum	133320.30	105611.20	27709.13***	2.44	0.01
Output(kg)	3808.29	3206.85	601.45**	2.31	0.02
Farm size	3.07	2.69	0.38	1.53	0.13
Income/per capital income	78037.74	73227.54	4810.21	0.50	0.61
Non-farm assets	138134.50	76102.50	62032.03**	4.5061	0.00
Farm assets	16289.39	11842.72	4446.68*	1.99	0.05
Area cultivated to cassava	2.09	1.66	0.43*	0.08	0.09

Source: IITA/DIVA Adoption and Impact Survey (2011)

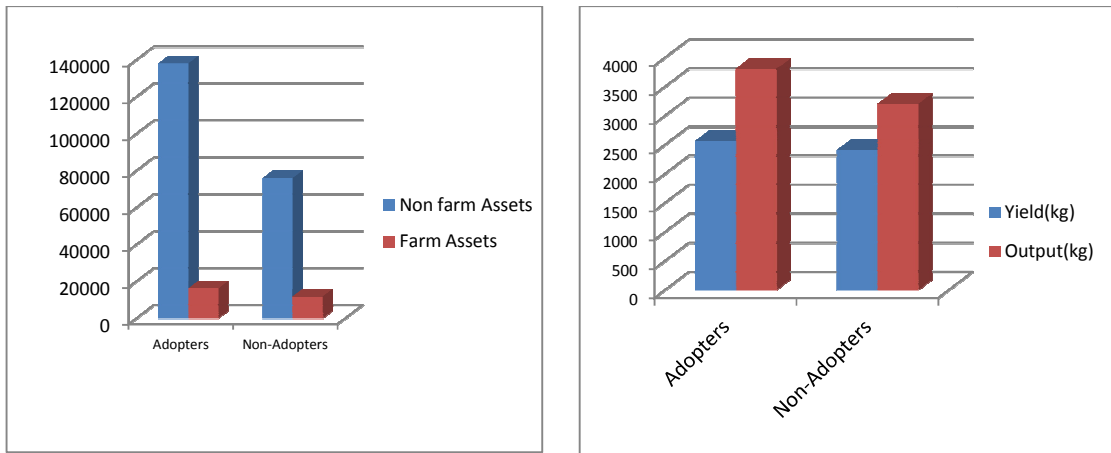


Fig. 1.

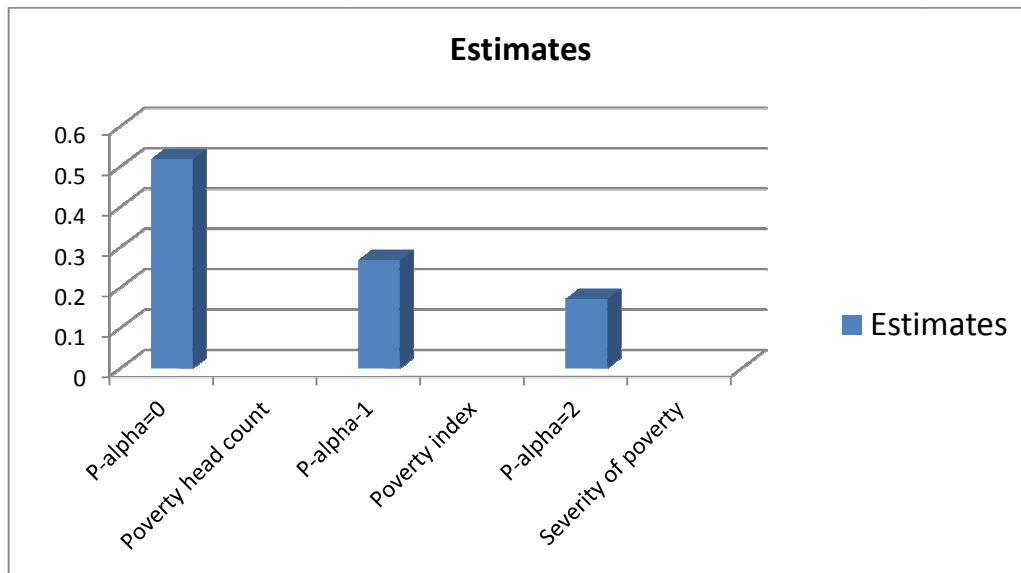


Fig. 2. Poverty indices among the sampled farmers

Source: IITA/DIVA Adoption and Impact Survey (2011)

There were positive and significant mean differences between the adopters and non-adopters in income, output, farm and non-farm assets and farm size. The average observed income per annum of adopters is more than the income of non-adopters. The table clearly showed the mean difference of N27709.13 between their incomes. So the adopters of improved cassava varieties are richer than the non-adopters by N27709.13. There is also difference in the output. The output of adopters is 601.45kg more than the non-adopters. This implies that the adopters are better-off than the non-adopters in all these aforementioned variables. In the case of random experiment, this

could be interpreted as the impact. However, in this study due to the selection bias resulting from the observable characteristics of the farmers, this result has no any causal interpretation. In order to provide a meaningful result of that has causal interpretation we adopted the PSM.

3.2 The Poverty Measures

Relative poverty line was used to compute the poverty line for the respondents and is defined as the two-third (2/3) of the mean per capital income of the farmers. The per capital income computed for this study as derived from the data was N 32575.50 hence the poverty line is N 21717.53.

The results as depicted in the Table 3 below shows that about 52% of the farmers is poor. Further estimate shows that the depth of poverty stood at 28% while the severity of the poverty is 17%. It then means that for the poor farmers to cross the poverty line they will need to increase their income by 27%.

3.3 Poverty Estimate by State, Gender and Improved Cassava Varieties Adoption Status

Result analysis in Table 4 shows that about 56% of the farmers' population in Osun state were poor while the proportion that were poor in Oyo state was about 48%. It thus means that poverty is higher among rural farmers in Osun State than Oyo State. Further estimate by gender showed that 63% of the female farmers were below poverty line while it was 50% in male farmers meaning that male farmers are richer than female farmers. Again, computing the poverty estimate by adoption status revealed that poverty is higher among non-adopters (57%) than among adopters (47%). All the poverty indices indicate

that poverty was more prevalent and severe among non-adopters compared to adopters.

3.4 Impact of Adoption on Productivity

Propensity Score Matching (PSM) was used to check the existence and robustness of the causal interpretation given to the association found between adoption of improved cassava varieties, higher yields and income obtained by farmers who have adopted improved cassava varieties. This causal impact of adoption of improved cassava varieties on farmers' productivity and income was done by selection of a very large number of observable factors. The robustness of the causal impact was done after controlling for selection on observable or characteristics. By implication, we can confidently attach causal interpretation to the impact of adoption of improved cassava varieties on cassava yields obtained by farmers. The ATT is the most important statistic of interest in this study and it is the difference in yields and income between the non-adopters and adopters after controlling for hidden selection bias.

Table 3. Poverty estimate by state, gender and improved cassava varieties adoption status
poverty estimate by state

Group	Estimate	STE	LB	UB	Poverty line
Osun	0.5631	0.0385	0.4874	0.6388	21717.53
Oyo	0.4789	0.0391	0.4021	0.5559	21717.53
Poverty estimate by gender					
Female	0.6346	0.0667	0.5035	0.7658	21717.53
Male	0.5025	0.0329	0.4379	0.5671	21717.53
Poverty estimate by adoption status					
Non-Adopters	0.5647	0.0388	0.4884	0.6409	21717.53
Adopters	0.4669	0.0392	0.3899	0.5441	21717.53

Source: IITA/DIVA Adoption and Impact Survey (2011)

Table 4. Impact of Improved cassava varieties adoption on productivity: PSM

Nearest neighbour matching (NNM)					
Variable	Adopter	Non-adopter	Difference	Std. error	T-stat
Unmatched	7.21	7.04	0.17	0.15	1.15
ATT	7.21	6.52	0.698***	0.23	3.06
ATU	7.04	7.55	0.51	-	-
ATE			0.59	-	-
Kernel based matching					
Unmatched	7.21	7.04	0.17	0.15	1.15
ATT	7.24	6.86	0.38***	0.16	2.47
ATU	7.05	7.38	0.33	-	-
ATE			0.35	-	-

Source: IITA/DIVA Adoption and Impact Survey (2011)

Results in Table 6 indicate the ATT is obtained using Nearest Neighbor Matching (NNM) and Kernel Based Matching (KBM) algorithms. These results indicated that adoption of improved cassava variety has a robust positive and significant impact on cassava yield. Becerril and Abdulai [11], Mendola [12] obtained similar results. Results in Table 6 shows that, on average, the increase in cassava yield after adoption of improved variety (ATT) is about 70% using NNM and it is about 38% using the KBM which means the adoption of improved cassava variety has caused the yield of cassava farmers to increase.

3.5 Impact of Adoption of Improved Cassava Varieties on Farmers' Income

In the same vein, PSM was used to check for the impact of adoption on the farmers' income. The result of the analysis of the impact of adoption of improved cassava variety on income and poverty status between adopters and non-adopters of ICVs is shown in the Table.7, below. As it is evident from the table, the incidence of poverty was higher among non- adopters as income of adopters was higher than that of the non-adopters by N43463.77.

In addition, by adoption of improved cassava varieties there is income increase on the part of adopters by 30% using the NNM, while the KBM also revealed that the adopters' income increased by 17% compared to that of the non-adopters. This shows that, irrespective of the matching method adopted, this study has been able to establish that improved cassava varieties had a positive impact on income of the farmers and therefore contributed to poverty reduction. This conforms to the finding of Souléïmane (2006). In the same vein, we found that the adoption of improved cassava varieties also have a significant poverty reducing effect of about 20% as shown in Table 5. Thus, adoption of improved cassava varieties did not only increase productivity, it also generates an increase in farmers' income with a significant reduction in the proportion of the farmers that were below the poverty line.

3.6 Impact of Adoption of ICVs on Poverty Status of Adopters

In order to evaluate the effect of adoption of ICVs on households' welfare a multivariate analysis was conducted using Heckman's two-stage model. The dependent variable of the adoption model was specified as binary which is equal to 1

Table 5. Impact of adoption of improved cassava varieties on farmers' income

Nearest neighbour matching (NNM)					
Variable	Adopters	Non-adopters	Difference	Std.Error	T-stat
Unmatched	133773.69	105611.21	28162.48	11392.57	2.47
ATT	133773.69	90309.92	43463.77***	13487.56	3.22
% impact	11.45	11.15	0.3012**	0.1160	2.59
ATU	105611.21	124876.72	19265.51	-	-
ATE			30848.05	-	-
Kernel based matching					
Variable	Adopters	Non-adopters	Difference	Std. Error	T-stat
Unmatched	133773.69	105611.21	28162.48	11392.57	2.47
ATT	130341.15	110123.94	20217.20**	11646.16	1.74
% impact	11.44	11.27	0.1686**	0.0911	1.85
ATU	105536.50	117736.52	12200.02		
ATE			16016.86		

Source: IITA/DIVA Adoption and Impact Survey (2011)

Table 6. Impact of improved cassava varieties adoption on poverty headcount

Variable	Adopters	Non-adopter	Difference	Std.Error	T-stat
Unmatched	0.46	0.66	-0.20	0.05	-4.00
ATT	0.46	0.66	-0.20**	0.07	-2.85
ATU	0.56	0.57	-0.01	.	.
ATE			-0.18	.	.

Source: IITA/DIVA Adoption and Impact Survey (2011)

Table 7a. Impact of adoption on productivity

	Coef.	Std. Err.	z	P>z
Household size	0.1192*	0.6717	1.77	0.076
Age	-0.0520	0.0821	-0.63	0.527
Occupation	0.1167	1.5612	0.07	0.94
Education in yrs	-0.0468*	0.0278	-1.69	0.092
Rented land	-0.2940	0.3328	-0.88	3.770
Total cost of labour	0.0000206**	7.3600	2.8	0.005
Own radio	-0.1559	0.3777	-0.41	0.68
Own television	-0.7403***	0.2558	-2.89	0.004
Own mobile	-0.5656**	0.2748	-2.06	0.04
Non-prodcasset	0.1337	0.2545	0.53	0.599
Total non-farm income	-3.9200	9.7100	-0.4	0.687
gender2	-0.4623	0.5184	-0.89	0.372
Total area cultivated this season	-0.2777***	0.0424	-6.56	0.000
Production assets	0.1688	0.1880	0.9	0.369
Credit access	-0.0067	0.3236	-0.02	0.983
Mills ratio	0.7178	3.4368	0.21	0.835
Determinants of adoption				
Extension contact	-0.0739	0.1840	-0.4	0.688
Institutional relationship	-0.0678	0.2104	-0.32	0.747
Household size	-1.9600	3.2700	-0.6	5.49E-01
Nonproduction asset	0.1153***	0.0466	2.47	0.013
Occupation	0.7939***	0.2475	3.21	0.001
Age	0.0326	0.0272	1.2	0.231
Education in yrs	-4.8200	1.6800	-0.29	7.7400
Total non-farm income	8.4200	6.1500	0.01	0.989
Gender	0.1540	0.2506	0.61	0.539
Total area cultivated this season	-0.0032	0.0282	-0.11	0.911
Production asset	0.0674	0.0766	0.88	0.379
Own radio	0.0093	0.2501	0.04	0.97
Rented land	-1.0600	1.6500	-0.64	0.521
Total cost of labour	2.6900	3.0000	0.9	0.369
Own television	-0.0077	0.1608	-0.05	0.962
Own mobile	-0.0037	0.1739	-0.02	0.983
Credit access	-0.0776	0.1719	-0.45	0.652
Number of obs	375			
Censored obs	192			
Uncensored obs	183			
Wald chi2(16)	89.69			
Prob > chi2	0.0000			

if farmers adopt ICV and 0 otherwise. The second stage of the analysis in the Heckman's model (Table 7a&b) estimates the factors that determine the farmers' yield and also test for selection bias by inserting the lambda obtained from the first stage of the Heckman's model which is probit model. Contact with extension agent and relationship with institution were used as the identification variables. These variables are assumed to influence the probability of adoption of ICVs and not the farmers' yield.

In this context, yield was used as a proxy for productivity hitherto welfare. This means any

variable that increases yield will definitely increase productivity and thereby increases the welfare of the family. In the first stage of the Heckman's model, the coefficients of occupation and non-production assets were positive and statistically significant. Farmer whose primary occupation is farming has higher probability of adopting improved cassava varieties than farmers whose primary occupation is not farming. In the same vein, there is positive relationship between adoption and total non-production asset. Farmers with higher non-production assets has higher rate of adoption. This could be traced to the fact that farmers who have other

Table 7b. Regression analysis table

Yield	Coef.	Std. Err.	t	P>t
House hsize	-0.0337	0.0376	-0.89	0.371
Age	-0.0161	0.0312	-0.51	0.608
age2	-0.00005	0.0003	-0.19	0.85
Occupation	0.1619	0.2693	0.6	0.548
Education in yrs	-0.0175	0.0193	-0.91	0.366
Rented land	-0.1055	0.1903	-0.55	0.58
Total cost of labour	1.6400***	3.4500	4.74	0.000
Own radio	-0.3061	0.2867	-1.07	0.286
Own television	-0.3843**	0.1854	-2.07	0.039
Own mobile	-0.4365**	0.1998	-2.18	0.030
Non-prodcasset	0.0817	0.0533	1.53	0.126
Total non-farm income	5.2200	7.0800	0.74	4.62E-01
gender2	-0.4245	0.2830	-1.5	0.134
Total area cultivated this season	-0.2392***	0.0328	-7.29	0.000
Production asset	0.1638*	0.0870	1.88	0.061
Credit access	-0.2750	0.1983	-1.39	0.166
Number of obs	375			
F(16, 358)	6.62			
Prob > F	0			
R-squared	0.2284			
Adj R-squared	0.1939			
Root MSE	1.4797			

assets that can be used as capital are willing to venture into new business in order to increase their stream of income hence adopt new innovation on time than farmers without non-production asset.

In the second stage of Heckamn's model analysis, the coefficient of total cost of labour and household size were positive and statistically significant which means higher labour increases the rate at which farm activities are performed and this in turn increases yield. The same process goes for household size, the larger the household size the higher the yield. This can be attributed to the fact that farm labor supply will increase due to large household size. Access to television and mobile phone has negative coefficients and this simply means yield and access to media are negatively related hence increase in access to television and radio leads to reduction in yield. This could mean that farmers spend useful time that they suppose to use for productive farming work in watching programs that are not educative on television and this has in a way reduce labor supply and will surely reduce productivity. But this result negates the findings of Naveed Jehan, et al (2014) that says access to media increases productivity. Didier Alia (2013) was of the opinion that farmer's productivity increases when listening to informative and educative programs on the crop he cultivates rather than entertaining

programs. The output of the diagnostic analysis revealed that the mill ratio also known as lambda is not statistically significant which implies that there is no problem of selection bias in the model being used for estimation hence we revert to use linear regression to determine the impact of adoption on yield. From the regression analysis, the coefficients of total cost of labour and production assets are positive and statistically significant. Hence a unit increase in the amount expended on labor and production assets leads to 0.0002 and 0.164 increments in the yield of improved cassava variety respectively.

4. SUMMARY, CONCLUSION AND RECOMMENDATION

Improved cassava varieties were developed with the aim of contributing to poverty reduction and improving food security through increased productivity of Cassava. This study provides an ex- post assessment of improved cassava varieties adoption on productivity, income and poverty reduction using a cross-sectional data collected in 2011 by IITA from randomly selected sample of 446 households in both Osun and Oyo state of Nigeria. Analysis of the socioeconomic variables of farm households revealed that the mean age was 52 years which means it's the experienced and fairly old farmers that are engaged in cassava production in the study area. It was also shown that timely and adequate

information on improved cassava variety through mass media has positive and significant effect on the adoption level of the farmers. This study reveals that the adopters are significantly different from the non-adopters in terms of observable characteristics such as: Age, income, output, farm size, household assets (farm and non-farm). The proportion of poor households is higher in Osun State (56%) than in Oyo State (48%). Non-adopters are poorer (56%) than the adopters (47%).

The result of the first stage of Heckman two stage model was showed that occupation of household head and non-production farm assets positively and significantly determine the adoption of improved cassava varieties in the study area. Farmer whose primary occupation is farming has higher probability of adopting improved cassava varieties than farmers whose primary occupation is not farming. Adoption of improved cassava varieties have positive and significant impact on productivity and farmers' income and thus capable of leading to a reduction in poverty. The result of the second stage of Heckman two-stage model also showed that the coefficient of total cost of labour and household size were positive and statistically significant and thus positively affect yield. The causal impact of improved cassava varieties adoption was estimated using PSM with two different matching methods to assess robustness of the results. This study however shows that whichever matching method is used, the adoption of improved cassava varieties has a positive and significant impact on productivity, income and overall reduction in the proportion of the households that are below the poverty line.

There are three main conclusions that can be drawn from the results of this study on the impact of improved cassava variety adoption on productivity and poverty reduction. First, the group of farm households that adopted has systematically different characteristics than the group of farm households that did not adopt when some key socio-economic and physical variables are compared. Second, both the propensity score matching and Heckman's two-stage model results suggest that adopters of improved cassava varieties have significantly higher income than non-adopters even after controlling for all confounding factors. Third, the regression result revealed that any marginal increment in total cost of labour and production assets will lead to yield increase and thereby reduce poverty. The results of all these three

analysis carried out showed that adoption of improved cassava variety reduces poverty significantly. The results from this study generally confirms the potential direct role of adoption of improved varieties on improving rural household welfare, as higher incomes from improved varieties leads to poverty reduction.

The analysis of the determinants of adoption shows house hold head occupation and non-production assets are key determinants for adoption. This implies the need for policy to strengthen government extension services in the rural areas to promote and create awareness about the existing improved cassava varieties since the major occupation in this study area is farming. Also, innovative cassava projects that could yield good profit on returns should be launched in the area as farmers are willing to try new business. The government and Non-Governmental Organizations (NGOs) will need to take the lead in technology promotion and dissemination at the early stages of technology initiation and in providing a conducive environment for effective participation of the rural farmers. Awareness campaigns for improved varieties and its availability at the right time (planting season) will accelerate and expand adoption.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

REFERENCES

1. National Bureau of Statistics (NBS). Nigeria, Abuja National Population Census (NPC). National Bureau of Statistics Official Gazette (FGP 71/52007/2,500 (OL24) Abuja; 2006. Available:<http://www.nigerianstat.gov.ng>
2. Omonona BT. Poverty and its correlates among rural farming households in Kogi State, Nigeria. Unpublished Ph.D. Thesis, University of Ibadan, Ibadan. Nigeria; 2001.
3. Oyekale AS, Adepoju AO, Balogun AM. Determinants of poverty among riverine rural households in Ogun State, Nigeria. *Studies of Tribes and Tribals*. 2012;10(2): 99–105.
4. Igbalajobi O, Fatuase AI, Ajibefun I. Determinants of poverty incidence among rural farmers in Ondo State, Nigeria. *American Journal of Rural Development*. 2013;1(5):131–137.

5. Foster JJ, Greer, Thorbecke E. A class of decomposable poverty measures. *Econometrica*. 1984;52:761–766.
6. Cochran W, Rubin D. Controlling bias in observational studies. *Sankhyā: The Indian Journal of Statistics, Series A (1961-2002)*. 1973;35:417–446.
7. Bassi L. Estimating the effects of training programs with nonrandom selection. *The Review of Economics and Statistics*. 1984;66:36–43.
8. Rosenbaum PR, Rubin DB. Constructing a control group using multivariate matched sampling methods that incorporate the propensity score. *American Statistician*. 1985;39(1):33–38.
9. Friedlander D, Greenberg DH, Robins PK. Evaluating government training programs for the economically disadvantaged. *Journal of Economic Literature*. 1997; XXXV:1809–1855.
10. Heckman J, Navarro-Lozano S. Using matching, instrumental variables and control functions to estimate economic choice models. *Review of Economics and Statistics*. 2004;86(1):30–57.
11. Becerril J, Abdulai A. The impact of improved maize varieties on poverty in Mexico: A propensity score matching approach. *World Development*. 2009; 38(7):1024–1035.
12. Mendola M. Agricultural technology adoption and poverty reduction: A propensity-score matching analysis for rural Bangladesh. *Food Policy*. 2007;32(3): 372–93.

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Peer-review history:
The peer review history for this paper can be accessed here:
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