Adoption of Drought Tolerance Maize Varieties for Africa, Productivity, Food Security and Welfare in Nigeria: An Ex-Post Impact Assessment

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Abstract

Adoption of improved agricultural technologies is vital to revolution of developing countries farming system and a path out of poverty and food insecurity. This study assess the impact of adoption of Drought Tolerance Maize Varieties (DTMVs) on productivity, welfare and food security using a data of 2305 rural households collected by International Institute of Tropical Agriculture (IITA). Overt bias and hidden biases were controlled using the Inverse Propensity Score Weighting (IPSW) and Local Average Treatment Effect (LATE), respectively. The LARF model was also used to account for the observed heterogeneity in the impact of DTMVs adoption across gender, incidence of drought, poverty status and by Agro-ecological zones. The results shows that combination of access to seed and awareness increase DTMVs adoption to 90%. All the poverty indices reduced among the adopters. The result of the LATE by LARF, which is the only one with causal interpretation in this study shows that the adoption of DTMVs positively and significantly increases maize productivity and welfare by 602 kg/ha, ₦3764.27, respectively. Food insecurity was also reduced significantly by -7.00%. The impact on productivity was positively and significantly higher among the male headed households (663.16kg/ha), moist savannah (717.20 kg/ha), poor farmers (692.99 kg/ha) and the farmers not affected by drought (618.13 kg/ha). While the impact on welfare was higher among the female headed households (₦9006.09), moist savannah (₦ 4042.08), non-poor farmers (₦ 3943.37) and those farmers not affected by drought (₦ 3900.71).. Clearly, adoption of DTMVs is important in the achievement of sustainable increase in maize productivity, and improvement of rural households' welfare in Nigeria. Therefore, programs that could improve the exposure and access to DTMVs seed, which are paramount in the adoption and diffusion of DTMVs should be promoted. In addition, in order to further enhance the performance of the DTMVs, we strongly recommend the provision of irrigation facilities, particularly in the drought prone areas.

Keywords: Drought, Maize, Productivity Food security, Poverty, Welfare, Nigeria

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1.0. Introduction

The demand for food will continue to growth in line with the growth in world population. This observed growing demand for food must be met against a backdrop of rising global temperatures and changing patterns of precipitation. The wide fluctuations in agricultural output that have occurred throughout human history attest to the fact that agriculture is an economic activity that depend largely on the vagaries of weather (Pandey and Bhandari, 2009). Several authors have also attested to the fact that agriculture is highly vulnerable to climate variability and extreme climate events such as drought are one of the leading causes of crop failure (Salinger et al., 1997; Dixon and Segerson, 1999; Vermeulen et al., 2012; Challinor et al., 2010; Mueller and Osgood, 2009). As a result of climate change, drought are becoming longer, harder and more frequent. The economic costs of drought can be enormous. Prolong drought has the potential to cause severe food crisis, hunger, malnutrition, therefore, Mitigating or reducing the impacts of drought has long-term benefits (Blocks et al, 2008; Hyman et al., 2008). Various studies (IPCC, 2007) have pinpointed Africa to be one of the most exposed continents to suffer the devastating effects of climate change and climate variability, with colossal economic impact.

Maize represents life to more than 300 million of Africa's most vulnerable people and is Africa's most important cereal crop (La Rovere et al, 2014). In SSA, maize is a staple food where 95% of the maize produced constitutes a significant part of the daily diet (Hogh-Hensen et al. 2007). Incidentally, maize is a crop that is highly susceptible to droughts. According to Fisher et al. (2015), around 40 % of Africa's maize-growing area faces occasional drought stress, resulting in yield losses of 10–25 %. About 25 % of the maize crop suffers frequent drought, with losses of up to half the harvest (CIMMYT, 2013). Estimated future maize losses from climate change in Latin America and Africa was $2 billion per year (Jones and Thornton, 2003).

To reduce vulnerability and improve food security, the Drought Tolerant Maize for Africa (DTMA) project has released about 160 DTMVs between 2007 and 2013. According to Fisher et al. (2015), the DTMVs have been bred using modern conventional methods, without genetic modification. In addition to drought tolerance, the varieties have other attractive traits, such as resistance to major diseases and high protein content. The DTMVs have similar labour requirements and seed costs as non-DTM commercial varieties. Importantly, some of the DTMVs also nitrogen use efficient. Although the switch from local to improved maize can be a catalyst for increasing farmers' use of other inputs, especially fertilizer, many Africa farmers grow improved maize varieties without fertilizer (Smale et al. 2011).

In spite of all these tremendous efforts, the accomplishment of the stated objectives of the DTMA project particularly in relation to productivity increase, food security and poverty reduction is yet to be documented. Questions on by how much productivity of maize has increased, what percentage of food insecurity has been cut or by how much poverty has reduced among the adopters of the DTM varieties in Nigeria has not been answered. It is therefore in an attempt to document the success of the DTMA project in relation to all the targeted objectives that this study was conducted.

The rest of the paper is organized as follows. Section 2 presents an overview of the DTMA project. The analytical framework and estimation techniques is presented in section 3. Section 4 presents the data and descriptive statistics. The results and discussion are presented in section 5. Section 6 summarizes the major findings and presents the policy implications.

2.0. An Overview of the Drought Tolerance Maize Varieties for Africa

Water is very crucial to the growth and development of crops. An increased frequency of droughts and floods is pronounced in Africa where there is high dependence on agriculture and a limited capacity to adapt mitigating technologies and/or policy (Collier et al. 2008). In particular, drought is one of the major factors militating against agricultural productivity especially in drought-prone ecologies. Empirical evidence revealed that soil moisture deficit especially during the reproductive phase can lead to drastic reduction in maize grain yield with an estimated yield loss of more than 15% of well-watered condition in susceptible varieties (Basseti and Westgate, 1993; 1994). In order to mitigate the adverse effects of drought on maize production in Africa, it therefore becomes necessary for plant breeders to find and incorporate drought tolerant genes into existing germplasm. Notable among these efforts is the breeding of the Drought Tolerant Maize for Africa (DTMA) which was funded by the Bill and Melinda Gates and jointly implemented by CIMMYT and IITA in broad partnership with national agricultural research and extension systems, seed companies, and non-governmental organizations.

The development and dissemination of the Drought Tolerance Maize Varieties builds upon previous successes and on-going research, and steps up the development of new maize varieties with dramatically improved levels of drought tolerance. The basic aim of the DTMV dissemination and adoption is to generate maize varieties with 1 t/ha yield potential under drought stress conditions, increase the average productivity of maize under smallholder farmers' conditions by 20–30% on adopting farms, and add grain with an annual average value of US$160–200 million in drought affected areas (Abdoulaye et al., 2011). The DTMV has been disseminated since 2007 in 13 African countries: Ethiopia, Kenya, Uganda, and Tanzania, in eastern Africa. Nigeria, Benin, Ghana, and Mali in western Africa. Zambia, Zimbabwe, Malawi, Mozambique and Angola in southern Africa.

The new DTMVs underwent extensive multi-location on-farm testing using a participatory Variety Selection (PVS) approach with farmers. Across the 13 DTMA countries seed delivery has been the responsibility of national agricultural research systems and public and private seed companies. The DTMA project used field demonstrations and field days to diffuse information on the new DTMVs Messages have been channelled via posters, radio and television broadcasts, and newspapers. In 2013 alone, more than 33,000 MT of seed had been delivered to farmers in the 13 SSA countries (CIMMYT, 2014). Community survey were also conducted to complement household survey data, capture essential qualitative information and data that are difficult to obtain through formal household surveys, and serve as a pilot application for potential expansion through the African region.

3.0 Analytical Framework and Estimation Techniques

A farmer's decision to adopt the DTMVs is based on the expected benefit. A rational farmer is expected to adopt any DTMVs if the benefit from adoption is greater than that of non-adoption. If we let the gain from adoption of DTM varieties to be H*, then H*>0 implies that the benefit from DTMVs adoption is greater than that of non-adoption. Observably, it is impossible for us to observe H*, however, we can express it as function of observable vector of covariates in a latent model presented below:

$$H_i^* = \varphi R_i + \omega_i \qquad H_i = 1\left[H_i^* > 0\right] \tag{1}$$

Where H_i is a binary indicator variable that equals 1 if a farmer is an adopter of DTM varieties and 0 otherwise. φ is a vector of parameters to be estimated, and R_i is a vector of household socio-economic/demographic characteristics, farm level and institutional variables and ω_i is an error term assumed to be normally distributed. The probability of adoption of DTM varieties can be expressed as:

$$\Pr(H_i = 1) = \Pr(H_i^* > 0) = \Pr(\omega_i > -\varphi R_i +) = 1 - F(-\varphi R_i), \quad (2)$$

F is the cumulative distribution function for ω_i. Different models such as logit or probit can be used to estimate equation (2) depending on the assumption made about the functional form of F. The adoption of DTMVs is expected to lead to increase in productivity, reduce food insecurity and poverty. We can link the decision to adopt with our expected outcomes, by considering a farmer that is risk-neutral with the ultimate aim to maximise his or her net returns, , subject to competitive input and output markets and a single-output technology that is quasi-concave I the vector of variable inputs, U. This exposition can be expressed as follows:

$$Max\pi = PQ(U, R) - I^{'}U \quad (3)$$

P is the output price and Q is the expected output level; I is a column vector of input prices, whereas U is a vector of input quantities and R represents farm level and household characteristics. The farm net returns can be expressed as a function of technology choice H, output price, variable inputs and household characteristics as follows:

$$\pi = \pi(H, I, P, R) \quad (4)$$

The reduced form equations for the input and output supply can be obtained by applying Hotelling's Lemma to equation (3) as follows:

$$U = U(H, I, P, R) \quad (5)$$

$$Q = Q(H, I, P, H) \quad (6)$$

The specifications in equations (4) to (6) reveal the choice of technology, input and output prices, as well as farm and household characteristics tend to influence farm net returns, demand for input and level of farm output. The relationship between technology adoption, food security and poverty reduction can be expressed as follows:

$$W_i = \phi_0 + \phi_1 H_i + \phi_2 R_i + \psi_i \quad (7)$$

W_i is a vector of outcome variables for household I, such as food security and poverty status of the household. R_i is the household characteristics, and ψ_i an error term, with ψ_i. There is a problem of selection bias if the error term (ω_i) in the technology choice equation (1) and the error term (ψ_i) of the outcome equation (7) are correlated and when this correlation is greater than zero, OLS regression techniques will tend to yield a biased estimates. This selection bias can be due to observable and un-observable characteristics of the farmers.

3.1 Inverse Propensity Score Weighting (IPSW) Techniques

In order to control for the selection bias due largely to observable and unobservable characteristics of the maize farmers, and provide a consistent estimates of the impact of adoption of the DTMVs on productivity, food security, poverty reduction and welfare we adopted the potential outcome framework proposed by Rubin (1974). Under this framework, individual maize farming household are believed to have two potential outcomes *ex-ante*: an outcome when adopting DTMVs denote by W_1 and an outcome when not adopting DTMVs denote by W_0. H is dichotomous variable that equals 1 if the farmer adopts DTMVs and zero otherwise. In this case the observed outcome W of any maize farming household can be presented as a function of W_1 and W_0 as follows:

$$W = HW_1 + (1-H)W_0$$

In a randomised control setting, the causal effect of DTMVs adoption on all our outcomes of interest would simply be the mean difference between the two potential outcomes: W_1 - W_0 However, under no circumstances can we observe the two potential outcome at the same time for an individual farmer. Meaning that a farmer cannot be an adopter and also be a non-adopter of DTMVs at the same time. Thus, making it practically impossible to calculate the effect of DTMVs adoption for an individual farmer. It however, possible for us to estimate the mean impact of DTMVs adoption for a population of maize farmers: $E(W_1 - W_0)$, where E is the mathematical expectation operator. This population parameter is referred to in the impact evaluation literature as the Average Treatment Effect (ATE). Another parameter that we can also estimate is the mean effect of adoption of DTMVs on the sub-population of adopters: $E(W_1 - W_0 | H = 1)$, which is popularly called the Average Treatment effect on the Treated and is usually denoted by ATE1 (or ATET). The average treatment effect on the *untreated*: $E(W_1 - W_0 \mid H = 0)$ denoted by ATEU is also another population parameter that can be defined and estimated.

The inverse propensity score weighing techniques (IPSW),(see Imbens, 2004; Lee 2005, Diagne, 2006; Diagne et.al., 2009; Dontsop-Nguezet et.al. 2011 and Awotide et.al., 2011) that is based on the Conditional Independence Assumption (CIA) was adopted in this study to control for the selection bias due to observable characteristics of the maize farmers. The IPSW is a two stage estimation procedure. In the first stage, the conditional probability of treatment $P(H = 1|\, R) \equiv P(\mathrm{R})$ (called the *propensity score)*, is estimated and ATE, ATE1 and ATE0 are estimated in the second stage by parametric regression-based methods or by non-parametric methods. Following Imbens, 2004; Lee, 2005; Hirano et al., 2000 and 2003; Diagne et al., 2009, Dontsop-Nguezet et al., 2011 and Awotide et al., 2013 we specified the IPSW techniques as follows:

$$AT\hat{E} = \frac{1}{m}\sum_{i=1}^{m}\frac{\left(H_i - \hat{p}(R_i)\right)W_i}{\hat{p}(R_i)\left(1-\hat{p}(R_i)\right)} \qquad (8)$$

$$AT\hat{E}T = \frac{1}{m_1}\sum_{i=1}^{m}\frac{\left(H_i - \hat{p}(R_i)\right)W_i}{\left(1-\hat{p}(R_i)\right)} \qquad (9)$$

$$AT\hat{E}U = \frac{1}{1-m_1}\sum_{i=1}^{m}\frac{\left(H_i - \hat{p}(R_i)\right)W_i}{\hat{p}(R_i)} \qquad (10)$$

Where m is the sample size, $m_1 = \sum_{i=1}^{n} H_i$ is the number of treated (i.e. the number farmers that adopted the DTMVs) and $\hat{p}(R_i)$ is a consistent estimate of the propensity score evaluated at R. Probit model was utilized in this paper to estimate the Propensity score.

3.2. Local Average Treatment Effect (LATE) Approach

In view of the fact that IPSW techniques can only control for the selection bias due to the observable characteristics of the farmers, we therefore in addition to the IPSW adopted a variant of the Instrumental Variable approach known as LATE to account for the selection bias due to the unobservable characteristics of the maize farmers and the Local Average Response Function (LARF) to take care of the non-randomness of the adoption variable and also to deal with the heterogeneity in the impact of DTMVs adoption in the population. Bias attributable to unobservable characteristics of the farmers is due to the fact that the farmers that adopted did because of anticipated benefits from adopting which we cannot observe. In addition, those farmers that adopted the DTMVs might be different in terms of inborn ability. Therefore identification and estimation the impact of DTMVs adoption, requires an instrument that is independent of these un-observed attributes of the farmers, but can only affect food security and poverty only through adoption of DTMVs.

For the estimation of the LATE estimate we used the simple non-parametric Wald estimator proposed by Imbens and Angrist (1994). This requires only the observed outcome variable *W*, the treatment status variable *H*, and an instrument *j*. In many studies of the impact of improved agricultural technologies adoption, awareness/exposure have been used as the instrumental variable to control for the unobservable characteristics of the farmers that influence adoption of DTMVs (Dontsop-Nguezet, 2011; Diagne et al., 2009). However, evidences from the adoption literature have shown that awareness is only a necessary, but not sufficient condition to guarantee adoption of improved technologies. Although, a farmer can be aware of the existence of any improved varieties like the DTMVs, but clearly adoption will be impossible without access to the seed of the DTMVs. Therefore, in this study in deviation from the past studies, we utilise access to seed as our instrumental variable. It is plausible to assume that access to seed only cannot impact productivity, food security or induce a reduction in poverty without adoption. Thus our instrumental variable satisfied the exclusive restriction condition for it to be a valid instrument.

Estimating the Treatment Effect using the instrument will gives us the LATE. This is because the treatment effect is local, since it only applied to the subset of farmers who are encouraged to adopt the DTMVs because of variation in the instrument (access to seed). The mean impact of the adoption of DTMVs on all our outcomes of interest among the sub-population of farmers that have access to seed (i.e. the LATE) is as given by Imbens and Angrist, 1994; Imbens and Rubin 1997, Lee, 2005:

$$LATE = E\left(w_1 - w_0 \mid h_1 = 1\right) = \frac{E\left(w \mid j = 1\right) - E\left(w \mid j = 0\right)}{E\left(h \mid j = 1\right) - E\left(h \mid j = 0\right)} \tag{11}$$

The denominator in equation (11) is the difference in the probability of adoption (probability of H=1) under the different values of the instrument. The right hand side of (11) can be estimated by its sample analogue:

$$LATE_{wald} = \left(\frac{\sum_{i=1}^{m} w_i j_i}{\sum_{i=1}^{m} j_i} - \frac{\sum_{i=1}^{m} w_i (1 - j_i)}{\sum_{i=1}^{m} 1 - j_i} \right) \times \left(\frac{\sum_{i=1}^{m} h_i j_i}{\sum_{i=1}^{m} j_i} - \frac{\sum_{i=1}^{m} h_i (1 - j_i}{\sum_{i=1}^{m} 1 - j_i} \right)^{-1} \qquad (12)$$

Estimation of equation (12) gives the effect of adoption of DTMV on the farmers whose adoption status changes as a result of the instrument. The description and definition of the variables used in the models is presented in Table 1.

3.4. Measuring Poverty Status

Following the adoption of Foster, Greer, Thorbecke (1984) (FGT) class of poverty measures, per capita total household expenditure was used to determine households' poverty status (Food Agricultural Organisation (FAO), 2003; Bamou and Mkouonga, 2008; Omonona and Agoi, 2007). This is defined as follows:

$$P_i = \frac{1}{N} \sum_{i=1}^{q} Gi \qquad (13)$$

Where:

$Gi = \left(\frac{Z - Yi}{Z} \right)$ = expenditure deficiency of household i

Headcount ratio (H)= $\frac{q}{N}$ (14)

Z=poverty line (2/3 mean per capita expenditure)

q = the number of households below the poverty line,

N = the total number of households in the total population

Yi = the per capita expenditure of household i

P = the extent at which a household is poor

4.0. Data and Sampling Framework

This study uses household survey data collected by International Institute of Tropical Agriculture (IITA) in Nigeria for the purpose of evaluating the impact of the DTMVs on important outcomes of interest. The survey was carried out in the course of November, 2014-February, 2015. One vital aspect of any credible impact assessment is a randomly selected, nationally representative sample. In order to achieve this, this study adopted the multistage stratified random sampling technique in order to obtain a nationally representative data, and also to ensure that at least one maize farmer is picked from each of the strata, even if the probability of being selected is far less than 1. In addition, this sampling technique reduces sampling error and can produce a weighted mean that has less variability than the arithmetic mean of a simple random sample of the maize famers' population in Nigeria. The States in Nigeria were divided into homogenous sub-groups based on the hectare of land devoted to maize production. This gave five groups, out of which 18 States were randomly selected. The selected 16 States contributed about 62.21 % to the total land size devoted to maize production in Nigeria. This shows that the selected States are major maize producing areas in Nigeria and can therefore nationally represent the maize farming households in Nigeria, hence allowing a generalization of the results to the whole nation.

The selection of the households is also random. Following National Bureau of Statistics (NBS) (2013) selection of the farming households for the Living Standards Measurement Study (LSMS) data, we obtained from the National Population Commission (NPC), Abuja the list of all the Enumeration Areas (EAs) in each of the selected States. The EAs was then divided by the number of Local Government Areas (LGAs) in each of the selected States to obtain the number of EAs per LGAs. After which we specifically focused on the crop farming households only. Following the National Bureau of Statistics (NBS) recommendation for a nationally representative data collection, we randomly selected 10% of the LGAs in each of the selected States and also satisfied the 95% confidence interval by selecting 5% of the total EAs per LGAs. From the list of communities obtained from the NPC, two communities were randomly selected from each of the EAs. Finally from the households in each of the selected EAs, five farming households were randomly selected

On the overall the sampling framework generated a total of 2305 farming households. In arriving at this sample size, account was taken of the constraints imposed by limitation of resources, the need to ensure a manageable and controllable sample structure and the three important levels at which data are required for any future agricultural development planning purposes, viz National, State and LGAs levels. Two pre-test of the survey instrument were conducted prior to the actual data collection process. This is to first ascertain whether the questions is actually well-structured, easily understood by the respondents and devoid of any ambiguity in language. Second it is also useful in determining the average time it will take to complete one questionnaire, this is useful in determining the number of days that would be required for the survey and also for the budget preparation. Among many others, the survey includes information on socio-economic/demographic characteristics of the households, household expenditure on food and non-food, output for maize and other notable crops, and income from various sources. The data was collected electronically using the “surveybe” software.

4.1. **Descriptive Statistics by Adoption Status**

The descriptive statistics of the farmers by adoption status is presented in Table 2. The result reveals that there is significant differences between the adopters of DTMVs and the non-adopters in many of the variables. Specifically, this result signifies that the adopters and the non-adopters are systematically different from each other. Meaning that comparison of our outcomes of interest without proper correction for these observables differences in the characteristics of the adopters and non-adopters will yield a bias estimate of the impact of DTMVs adoption on all our outcomes of interest.

5.0. Results and Discussion

5.1. Exposure, Access to seed, and Adoption Incidence Rate

The results presented in this section reveal (Table 3) that about 29% of the maize farmers interviewed for this study were exposed/ aware of the DTMV and adoption rate is 23% among the entire population of the farmers sampled. However, adoption rate (79%) was very high among the exposed or aware farmers in the sample. This indicates that awareness of the DTMV is highly important to achieve high rate of adoption and diffusion of the DTMVs in Nigeria. In the same vein, the results also shows that about 52% of the maize farmers have access to improved seed and adoption of the DTMVs among those farmers that have access to seed was approximately 44%, which is higher than the adoption rate of 23% in the population. This is an indication that apart from awareness or exposure, access to seed is another vital variable in adoption and diffusion of the DTMVs. It is obvious that no farmer can possibly adopt any of the varieties without first being exposed or aware of it and also have access to the seed. Thus, suggesting that awareness and access to seed are two major determinants of the DTMVs adoption in Nigeria.

In addition to assessing the influence of awareness and access to seed separately on adoption of the DTMVs, we also examined the rate of adoption among those farmers that are aware and at the same time have access to seed (i.e interaction of awareness/exposure and access to seed). We find that the adoption rate increased tremendously. Indicating that a combination of these two variables will give us about 90% adoption rate of the DTMVs in Nigeria. Thus, it is important to combine awareness with access to seed in order to achieve a universal adoption of the DTMVs.

5.2. Determinants of Access to Seed and DTMVs Adoption

The results from the probit model used to examine the factors affecting the access to seed (column1) and DTMVs adoption (Column 2) in Nigeria using maximum likelihood estimation are presented in Table 4. The log-likelihood of-942.26, the Pseudo R2 of 0.23 and the LR (Chi2) of 563.33 (significant at 1% level), for the adoption model implies that the overall model is fitted and the explanatory variables used in the model were collectively able to explain the farmers' decision regarding the adoption of DTMVs in Nigeria. In the same vein, the log-likelihood of-1466.52 , the Pseudo R2 of 0.06 and the LR (Chi2) of 196.57 (significant at 1% level),for the adoption model implies that the overall model is fitted and the explanatory variables used in the model were collectively able to explain farmers' access to seed in Nigeria.

Among the socio-economic characteristics of the farmers, farm size, roofing sheet, access to electricity, willingness to take risk, positive influence farmers' access to seed in the study area. In addition, access to seed is higher among the farmers from North West, South East and North East geopolitical zone. In the same vein, adoption of DTMVs is positively and significantly influence by maize yield, farm size, distance to the nearest sources of seed, access to electricity. In addition, adoption of DTMVs is higher among the female headed households, younger farmers, those farmers that are always willing to take the risk in trying new improved seeds varieties, those farmers affected by incidence of drought, and the farmers from North West and South East geopolitical zones.

5.3. Food Security and Poverty Status of the Respondents

Food is essential for survival and for mental and physical development and for the very poor, obtaining a minimum amount of calories becomes a dominant survival activity. Thus, being food secure is one of the main goals of national growth and development strategies**.** Food security has been identified as having food availability, food accessibility, utilization and stability of food access as its elements (Gross, et. al; 1999; Okuneye, 2002; Obamiro, et al, 2003; Amaza et.al, 2006; Titus et.al, 2007; and Watts, 2013). Food security at household level is a subset of the national level and it requires that all individuals and households have access to sufficient food either by producing it themselves or by generating sufficient income to demand for it (Otunaiya and Ibidun, 2014). Therefore, designing a solution that can conquer the prevailing food insecurity and poverty situation currently ravaging many developing countries particularly in SSA requires a robust information about the role of improved varieties, especially those that are resistance to drought in achieving food security and poverty reduction.

As presented in Table 5 above, about 14 % of the total respondents reported lack of enough food to eat in the last 12 months immediately preceding the survey, while the figure was 6 % and 16% among the DTMVs adopters and non-adopters, respectively. This shows that food shortage is more prominent and rampant among the non-DTMVs adopters than the DTMVs adopters. The poverty analysis of the respondents (Table 6) was computed using per capita household expenditure on food and non-food and the result shows that all the poverty indices are higher among the non-adopters compare with the adopters. Poverty headcount, depth and severity is lower among the DTMVs adopters. Hence, we can say that DTMVs adoption have the probability of generating a reduction in poverty.

5.4. Descriptive Statistics of the Impact of Adoption of DTMVs

Some variables that could serve as welfare and poverty indicators were selected and assessed for any significant differences between the adopters and non-adopters using t-test. The results of the analysis is presented in Table 7. The results show that in all the variables examined; except for per capita food expenditure, the adopters of DTMVs are better-off than the non-adopters. For the case of the per capita food expenditure, the result implies that the non-adopters appear to spend more money on the purchase of food compared with the non-adopters. This could be due to the fact that the adopters have more output out of which they consume and hence reduce the need to spend their income on food purchase. These results do not signify the impact of DTMV adoption, it only serve as a pointer to the fact that adopting DTMV could influence changes in the welfare or poverty status of the adopters. Observably, these observed results could be due attributed to other factors that may not be related to the adoption of DTMVs. Hence, in order to show a consistence impact of the adoption of DTMVs on food security and poverty reduction, we need methodologies such as IPSW and LATE that can allow us to give a causal interpretation to our results.

5.5. Econometric Impact of DTMVs Adoption on Maize Productivity

The impact of DTMVs adoption on maize productivity is presented in Table 8. We adopted various estimation techniques to provide answers to the question of whether the adoption of DTMVs have any impact on productivity. First, we examine the significance of the difference in the mean productivity between adopters and the non-adopters. The estimation of the mean difference shows a positive and significant increase of 610.51 kg/ha in maize productivity attributed to the adoption of DTMVs. However, this results does not have any causal interpretation in the absence of Randomised Control Trial (RCT) approach.

We also used the Inverse Propensity Score Weighting (IPSW) techniques that eliminate selection bias due to observable characteristics of the farmers. The result of the IPSW technique also reveals a significant positive impact of DTMVs adoption on maize productivity in the entire population of the sampled farmers. However, our interest is specifically on the impact of adoption of DTMVs on the adopters (ATET), which is 649.56 kg/ha. This implies that, the adopters have approximately 650kg/ha increase in productivity due to the adoption of DTMVs in Nigeria. The result also shows a potential increase in productivity of about 772kg/ha for the non-adopters if they had adopted the DTMVs. Just like the mean difference, the estimates of the IPSW also has no causal interpretation due to the presence of unobservable characteristics of the farmers which need to be controlled for. Therefore, in order to provide a consistent estimate of the impact of DTMVs adoption on productivity, we adopted the Local Average Treatment Effect approach; a variant of instrumental variable estimation techniques to impact evaluation, using access to seed as our instrument. We estimated the LATE by Wald and also by LARF due to the non-randomness of the adoption variable. We found that the adoption of DTMVs exerted a significant and positive impact of about 602.68kg/ha on productivity. Thus, we can conclude that adoption of DTMVs can lead to increase in maize productivity.

5.6. Heterogeneity of the Impact of Adoption of DTMVs on Productivity

AS shown in Table 9, the result of the analysis established the presence of heterogeneity in the impact of DTMVs adoption in Nigeria by gender, incidence of drought, poverty status, and Agro-Ecological Zones (AEZ). The results show that the impact is higher among the male headed households (663.16 kg/ha) than the male headed households (83.46 kg/ha). This is quite expected as the female headed households are reportedly very weak in their access to other vital productive resources such as credit and are poorer than the male headed counterparts. In the same vein, the result also shows that adoption of DTMVs have significant positive impact on both the poor and non-poor households. However, the impact was higher among the poor (692.99 kg/ha) than the non-poor (533.18kg/ha). This is an indication that the adoption of the DTMVs is actually pro-poor. In addition, it also have significant positive impact on maize productivity across all the two notable Agro-Ecological Zones (AEZ) (Dry and moist savannah). However, the impact was higher in the moist savannah (717.20 kg/ha) compare with the dry savannah (499.49 kg/ha). This implies that even thou the DTMVs perform well in drought prone areas, its performance could be better enhanced if there is irrigation facilities.

5.7. Impact of Adoption of DTMVs on Welfare

Per capital expenditure was used in this study as proxy for welfare measurement. The analysis of the impact of adoption of DYMVs on welfare is presented in Table 10. Using various means of impact evaluation, we found that adoption of DTMVs significantly impacted the rural farming households' welfare. Specifically, we observed a positive and significant mean difference of ₦3128.08 in per capita expenditure between the adopters and non-adopters. This implies that the per capita expenditure of the adopters is ₦3128.08 higher than the non-adopters. The result of the IPSW also reveals an Average Treatment Effect on the Treated (ATET) of ₦1954.69. This is interpreted as the increase in the per capita expenditure among the population of the adopters attributable to the adoption of DTMVs. The impact in the population of the farmers that have access to seed (LATE) estimated by LARF shows a significant positive increase in per capita expenditure of ₦3764.29. The result of the LATE has a causal interpretation in this study. Essentially, it shows that adoption of DTMVs have significant positive impact on the rural farming households welfare in Nigeria.

5.8. Heterogeneity in the Impact of Adoption of DTMVs on Welfare

The result also shows a very pronounced heterogeneity in the impact of adoption of DTMVs on welfare across gender, and incidence of drought, poverty status, and Agro-Ecological zones (AEZs) (Table 11). It is worthy of note that adoption of DTMVs is also pro-poor, as it has a significant positive impact of ₦3549.50 on the poor farming households, even though the impact on the non-poor farming households' welfare (₦3943.37) seems to be larger. In terms of its impact across the AEZs, it has the higher positive and significant impact in the moist savannah (₦4042.08) compared with the dry savannah (₦3520.57). On the overall, adoption of DTMVs has positive impact on rural farming households' welfare in Nigeria.

5.9. Impact of DTMVs Adoption on Food Security index

The impact of DTMVs on food security is presented in Table 12. The result shows that adoption of DTMVs have the probability to significantly reduces food insecurity by -7.33% in the entire sampled population. We also observed heterogeneity in the impact of DTMVs adoption in the population. For instance, the result shows that DTMVs adoption reduces food insecurity significantly by -36.36% among the female headed households, while it shows no significant impact among the male headed households. In the same, the food insecurity reduces by -9.48 % among those households affected by drought. The impact across the six geopolitical zones reveals significant food insecurity reduction in the South-South (-22%), South East (-19.39%) and South West (-23.29%) with no significant impact in the other norther regions. The reason could be due to the fact that the Norther regions are the chronically drought prone areas and hence, have been badly affected by drought prior to the dissemination of the DTMVs. It will therefore require many more years of consistent adoption and wide diffusion for any visible positive impact to be achieved. In addition, it also implies that even though DTMVs were basically developed for drought-prone areas, it performs even better in less dry areas.

5.10. Estimated Coefficients of the LARF for Maize Productivity, Food Security Index and Per capita Food Consumption Expenditure

The results of the determinants of productivity, per capita consumption expenditure and food security index as reveal by the LARF estimate are presented in Table 13. The study disaggregated the explanatory variables into two different groups: the non-interacted terms and the interacted terms. The non-interacted terms are the dependent variables that explains the variation in productivity, per capita consumption expenditure and food insecurity.

The result shows that apart from DTMVs adoption, other socio-economic and demographic characteristics of the farmers also positively and significantly determine the productivity, per capita consumption expenditure and food insecurity. For instance, gender, household size and education positively and significantly determine productivity. The per capita consumption expenditure is positively, statistically and significantly determine by gender of the household head and farm size, and negatively by household size. Food insecurity is significantly reduced by age of household head, farm size, gender of household head and years of formal education.

The interacted term for age of household head, farm size, is positive and statistically significant for productivity. This implies that the impact of DTMVs adoption on productivity will be higher for those farmers whose households' head are old. The result further shows that the impact on productivity and per capita consumption expenditure would be higher among the female headed households compare with the male counterparts.

The interacted term for age of household head, is negative and statistically significant for food insecurity. This suggest that the impact of DTMVs adoption on food insecurity will be smaller for those farmers whose household heads are young. The positive and statistically significant of the interacted term for household size suggests that the impact on food insecurity will be higher among those farmers with large household size.

6.0. Summary, Conclusion and Policy Recommendations

This study assesses the impact of adoption of DTMVs on productivity, food security, poverty and welfare among maize farming households in Nigeria. We adopted various impact assessment methodologies as a form of robustness check and also to provide a consistent estimates of the impact of adoption of DTMVs on all our outcomes of interest. Specifically, we used the IPSW and the LATE estimates by Wald and by LARF.

The results show that DTMVs adoption rate in the population was 23 %, while adoption rate in the population of the exposed farmers was 79 %, and 44 % in the population of the farmers that adopted DTMVs because they have access to seed. Interestingly, however the combination of exposure and access to seed yielded a very high adoption rate of about 90 %. Incidence, depth and severity of poverty reduced among the adopters. The test of mean difference reveals that the adopters have significant and statistically higher maize output, maize yield, income from maize production, per capita non-food expenditure and expenditure on agricultural production than the non-adopters. DTMVs adoption increase productivity, per capita consumption expenditure and reduces food insecurity significantly. We also observed higher impact among the male headed households in all our outcomes of interest. Finally, the results also show that the socio-economic characteristics of the farmers also affected the productivity, per capita consumption expenditure and food insecurity index.

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Appendix:

Table 1: Description and definition of the variables used in the models.

Variable	Definition	Mean	SD
DTMA Adoption	1 if farmer adopted DTMV, 0 otherwise	0.2287	0.4201
Awareness of DTMA	1 if farmer is aware of DTMV, 0 otherwise	0.2909	0.4543
Age	Age of household head in years	48.00	13.26
Gender	1 if household head is male, 0 if female	0.8783	0.3269
Household size	Number of people living and eating together	7.18	4.62
Education	Years of formal education	7.72	6.63
Farm size	Total cultivated farmland		
Distance (Km)	Average distance to the nearest sources of seed	17.52	17.01
Residence	Years of residence in the village	40.74	17.57
Farming experience	Years of farming experience	27.87	14.94
Illiterate	1 if farmer has formal education, 0 otherwise	0.1568	0.3637
Land ownership	1 if farmer is the owner of the farmland, 0 otherwise	0.8389	0.3677
House ownership	1 if farmer owns a house	0.8663	0.3404
Seed access	1 if farmer has access to improved seed	0.5239	0.4995

Source: IITA-DTMA Survey, 2015

Table 2: Descriptive Statistics of the Maize Farmers by DTMVs Adoption Status

Variable	Pooled data (N=2334)	Adopters (N=554)	Non-adopters (N= 1800)	Mean difference	t-test
Socio-Economics characteristics					
Age of household head (years)	47.45 (0.289)	45.313 (0.675)	48.086 (0.675)	2.773 (0.686)	4.04***
Household size (number)	7.176 (0.096)	7.722 (0.186)	7.013 (0.111)	0.708 (0.228)	3.11***
Farm size (Ha)	4.42 (0.068)	5.034 (0.151)	4.235 (0.075)	0.800 (0.159)	5.02***
Education (Years)	7.505 (0.132)	6.754 (0.266)	7.732 (0.151)	0.978 (0.312)	3.14***
Distance to seed (KM)	17.519 (0.605)	17.065 (0.359)	17.627 (0.676)	0.562 (1.532)	0.37
Main occupation(farming=1)	0.866 (0.007)	0.787 (0.018)	0.769 (0.009)	0.017 (0.021)	0.83
Years of farming experience	27.876 (0.323)	25.526 (0.699)	28.559 (0.363)	3.034 (0.771)	3.93***
Food scarcity (yes=1)	0.177 (0.009)	0.113 (0.019)	0.189 (0.010)	0.076 (0.024)	3.11***
Household Endowments (Quality of Life)					
Ownership of farmland (yes=1)	0.839 (0.008)	0.897 (0.013)	0.822 (0.009)	0.075 (0.018)	4.17***
House painted (yes=1)	0.242 (0.009)	0.299 (0.019)	0.225 (0.009)	0.074 (0.024)	3.47***
Roofing sheet (Yes=1)	0.864 (0.007)	0.931 (0.011)	0.844 (0.009)	0.086 (0.017)	5.14***
Access to potable water (yes=1)	0.354 (0.009)	0.438 (0.022)	0.329 (0.011)	0.109	4.66***
Access to electricity (yes=1)	0.469 (0.010)	0.551 (0.022)	0.444 (0.012)	0.106 (0.025)	4.33***
Institutional variables					
Access to credit (yes=1)	0.153 (0.008)	0.103 (0.013)	0.168 (0.009)	0.065 (0.018)	3.66***
Membership of organisation (yes=1)	0.656 (0.010)	0.524 (0.023)	0.693 (0.011)	0.169 (0.024)	7.01***

Note: Legend: * significant at 10%; ** significant at 5% and *** significant 1%
Figure in parentheses are the standard errors
Source: IITA-DTMA Field Survey, 2015

Table 3: Exposure, Access to seed, interaction of adoption and access to seed and Adoption Incidence Rate

Variables	parameter	Robust Std. Err.	z	P>z
Observed Sample Exposure and Adoption Incidence Rate				
Exposure/N	0.291***	0.009	30.94	0.000
Adoption /N	0.229***	0.009	26.31	0.000
Adoption/Exposure	0.787***	0.029	26.31	0.000
Observed Sample Access to Seed and Adoption Incidence Rate				
Access to seed / N	0.524***	0.010	50.68	0.000
Adoption /Access to seed	0.437***	0.017	26.31	0.000
Observed Sample Interaction of Exposure and Access to seed and Adoption Incidence Rate				
Exposure and seed access/ N	0.255***	0.009	28.28	0.000
Adoption/exposure and access to seed	0.896***	0.034	26.31	0.000

Note: N= Number of observation

Table 4: Determinants of Access to Seed and DTMVs Adoption

	(1) Access to Seed	(2) Adoption
Variables	Coefficient	Coefficient
Household size	0.003 (0.006)	0.009 (0.008)
Age of household head (year)	0.001 (0.002)	-0.006** (0.003)
Main occupation (farming=1)	0.009 (0.069)	0.024 (0.086)
Maize yield (kg/ha)	0.000 (0.000)	0.000*** (0.000)
Education (year)	0.001 (0.005)	-0.007 (0.006)
Farm size (ha)	1.91E-02* (9.90E-03	0.038*** (0.012)
Distance to seed source (km)	0.003 (0.003)	0.009*** (0.004)
Income from maize (N)	3.32E-07(2.11E-07)	3.57E-07 (2.49E-07)
Access to credit (yes=1)	0.036 (0.078)	-0.055 (0.102)
Roofing sheet (yes=1)	0.238*** (0.091)	0.147 (0.123)
Access to electricity (yes=1)	0.228***(0.059)	0.197*** (0.069)
Affected by drought (yes=1)	0.074(0.071)	0.148* (0.088)
North West	0.386 ***(0.079)	1.122*** (0.096)
South South	-0.452 ***(0.145)	0.046 (0.206)
South East	0.724 ***(0.153)	1.387*** (0.154)
North Central	-0.319 ***(0.080)	-0.269** (0.114)
North East	0.269*(0.144)	-0.808*** (0.305)
Willingness to take risk (yes=1)	0.123 *(0.065)	0.287***(0.076)
Gender (male=1, female=0)	-0.106(0.097)	-0.298 (0.119)
Constant	-0.695***(0.183)	-2.015***(0.235)
Number of observation	2265.00	2265.00
Prob >chi2	0.0000	0.0000
LR chi2 (18)	196.57	563.33
Pseudo R2	0.028	0.2301
Log likelihood	-1466.52	-942.27

Source: IITA-DTMA Field Survey, 2015

Table 5: Food Shortage in the Past 12 months

Food Shortage	Frequency	Percentage
Pooled data		
No	2013.00	86.25
Yes	321.00	**13.75**
Total	2334	100.00
Adopters		
No	501.00	93.82
Yes	33.00	**6.18**
Total	534.00	100.00
Non-adopters		
No	1512.00	84.00
Yes	288.00	**16.00**
Total	1800.00	100.00

Source: IITA-DTMA Field Survey, 2015

Table 6: Poverty Status

Poverty Index			
poverty Headcount (P_0)	0.4622	O.4194	0.4749
Poverty Depth (P_1)	0.2035	0.1748	0.2121
Poverty Severity (P_2)	0.1223	0.1005	0.1289

Source: IITA-DTMA Field Survey, 2015

Table 7: Descriptive Statistics of the Impact of Adoption of DTMVs

Variable	Pooled data (N=2334)	Adopters (N=554)	Non-adopters (N= 1800)	Mean difference	t-test
Maize output (kg)	3656.13 (81.79)	5430.13 (180.70)	3131.14 (87.79)	2298.99 (188.85)	12.17***
Maize Yield (kg/ha)	1152.09 (26.70)	1621.64 (61.32)	1011.13 (28.59)	610.51 (62.06)	9.84***
Maize Income (₦)	193385.10 (15157.76)	267593.50 (54735.74)	171357.70 (11029.21)	96235.86 (36032.41)	2.67***
Per capita maize income (₦)	31949.16 (2408.01	44144.90 (8918.49)	28291.15 (1618.68)	15853.76 (5707.05)	2.78***
Total farm income (₦)	1060276.00 (859025.30)	3998079.00 (3754241.00)	188728.10 (13955.90)	3809351.00 (2043948.00)	1.86*
Per capita total expenditure ₦)	25326.52 (420.32)	27734.88 (859.77)	24606.80 (480.47)	3128.78 (996.70)	3.14***
Per Capita Food expenditure (₦)	4329.62 (179.02)	4002.71 (152.34)	4427.62 (86.72)	424.91 (179.02)	2.37**
Per capita non-food expenditure (₦)	18426.48 (13449.40)	62754.90 (58295.61)	5138.28 (468.62)	57616.62 (31912.20)	1.81*
Total agricultural expenditure (₦)	122743.40 (3264.84)	154708.50 (7974.90)	113260.40 (3480.73)	41448.07 (7726.54)	5.36***
Cost of fertilizer (Maize) (₦)	39092.54 (1521.38)	62281.11 (4354.25)	32213.26 (1452.83)	30067.85 (3568.73)	8.43***
Cost of fertilizer(Other crops) (₦)	56682.16 (3658.79)	91646.62 (6414.47)	46309.38 (4316.56)	45337.24 (8661.40)	5.23***

Note: Figures in parentheses are the standard error and *, **, ***, significant at 10%, 5% and 1%, respectively.
Source: IITA-DTMA Field Survey, 2015

Table 8: Econometric Impact of DTMVs Adoption on Maize Productivity

Estimation	Parameter	Robust std. Error	Z-value
Estimation by Mean Difference			
Mean Difference	610.51***	67.63	9.03
Adopters	1621.64***	61.29	26.46
Non-adopters	1011.13***	28.59	35.35
Inverse Propensity Score Weighting Estimation			
ATE	743.28***	77.80	9.55
ATET	649.56***	73.01	8.87
ATEU	772.01***	83.09	9.29
Local Average Treatment Effect Estimation			
LATE by WALD estimators	455.12	168351.30	0.000
LATE by LARF	602.68***	176.26	3.42

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

Source: IITA-DTMA Field Survey, 2015.

Table 9: Heterogeneity in the Impact of Adoption of DTMVs on Productivity

Estimation	Parameter	Robust std. Error	Z-value
Impact by Gender			
Male	663.16***	146.66	4.52
Female	83.46	1009.08	0.08
Impact by Incidence of Drought			
More prone to drought	521.32***	147.72	3.53
Less prone to drought	618.13***	186.49	3.33
Impact by Agro-Ecological Zone			
Dry Savannah	499.49**	189.46	2.64
Moist Savannah	717.20***	186.25	3.85
Impact by poverty Status			
Poor	692.99***	174.32	3.98
Non-poor	533.22**	185.41	2.88

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

Source: IITA-DTMA Field Survey, 2015.

Table 10: Impact of Adoption of DTMVs on Welfare

Estimation	Parameter	Robust std. Error	Z-value
Estimation by Mean Difference			
Observed Difference	3128.08***	984.56	3.18
Adopters	27734.88***	859.32	32.28
Non-adopters	24606.80***	480.55	51.21
Inverse Propensity Score Weighting Estimation			
ATE	2121.77**	983.71	2.16
ATET	1954.69**	930.15	2.10
ATEU	2171.70**	1036.70	2.09
Local Average Treatment Effect Estimation			
LATE by WALD estimators	35502.02	767763.30	0.01
LATE by LARF	3764.29***	182.32	20.65

Legend: Significance level **P<0.05, *P<0.10, *** P<0.01.
Source: IITA-DTMA Field Survey, 2015

Table 11: Heterogeneity in the Impact of Adoption of DTMVs on Welfare

Estimation	Parameter	Robust std. Error	Z-value
Impact by Gender			
Male	3148.78***	182.04	17.30
Female	9006.09***	192.69	46.74
Impact by Incidence of Drought			
More prone to drought	3009.67***	342.27	8.79
Less prone to drought	3900.71***	160.04	24.37
Impact by Agro-Ecological Zone			
Dry Savannah	3520.57***	89.41	39.37
Moist Savannah	4042.08***	318.89	12.68
Impact by poverty Status			
Poor	3549.50***	227.42	15.61
Non-poor	3943.37***	162.95	24.35

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

Source: IITA-DTMA Field Survey, 2015.

Table 12: Impact of DTMVs Adoption on Food Security index

Estimation	Parameter	Robust std. Error	Z-value
Estimation by Mean Difference			
Observed Difference	-0.0394	0.0456	-0.86
Adopters	0.5902***	0.0410	14.38
Non-adopters	0.6297***	0.0199	321.52
Inverse Propensity Score Weighting Estimation			
ATE	-0.0607	0.0478	-1.27
ATET	-0.0678	0.0451	-1.50
ATEU	-0.0589	0.0500	-1.18
Local Average Treatment Effect Estimation			
LATE by WALD estimators	-0.0028	29.212	-0.00
LATE by LARF	-0.0733*	0.0428	-171
Impact by Gender			
Male	-0.0543	0.0446	-1.22
Female	-0.3636***	0.1308	-2.78
Impact on farmers affected by drought	-0.0948**	0.0462	-2.05
Impact by poverty Status			
Poor	-0.0292	0.0483	-0.60
Non-poor	-0.1121**	0.0463	-2.42
Impact by Geopolitical Zone			
North West	-0.0522	0.0457	-1.14
North Central	0.0117	0.0523	0.22
North East	-0.0899	0.0575	-1.56
South South	-0.2190***	0.0542	-4.04
South East	-0.1939***	0.0543	-3.57
South West	-0.2329***	0.0574	-4.06

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

Source: IITA-DTMA Field Survey, 2015

Table 13: Estimated Coefficients of the LARF for Maize Productivity, Food Security Index and Per capita Expenditure

Variable	(1) Productivity	(2) Per capita Consumption expenditure	(3) Food insecurity index
Non-Interacted Variables			
Adoption	6.929*** (0.601)	9.810 *** (0.240)	-1.552 (1.201)
Gender	7.781*** (0.266)	9.032*** (0.206)	-0.202** (0.099)
Health status	-0.363***(0.101	-0.143** (0.072)	-0.025 (0.059)
House ownership	-0.038 (0.144)	-0.221** (0.098)	0.171* (0.093)
Age	-0.008 **(0.004)	0.003 (0.003)	-0.007*** (0.002)
Farm size	-0.144*** (0.028)	0.047*** (0.010)	-0.046*** (0.012)
Household size	0.025*** (0.008)	-0.125*** (0.015)	0.027*** (0.004)
Education	0.015* (0.008)	0.002 (0.007)	-0.013** (0.005)
Interacted Variables			
Gender	-7.710*** (0.393)	-9.432*** (0.253)	0.457 (0.330)
Health status	0.391** (0.164)	0.079 (0.143)	0.157 (0.141)
House ownership	0.656 (0.536)	-0.172 (0.181)	1.026(1.1556)
Age	0.010*(0.006)	0.006 (0.005)	-0.011* (0.006)
Farm size	0.099***(0.036)	0.006 (0.022)	0.013 (0.024)
Household size	-0.026 (0.017)	-0.035 (0.028)	0.037***(0.013)
Education	-0.028 (0.015)	-0.006 (0.016)	0.005 (0.013)
R-Squared	0.5106	0.6751	0.6851
Adjusted R-Squared	0.4999	0.6680	0.6680

Legend: Significance level **P<0.05, *P<0.10, *** P<0.01. Source: Field Survey, 2009
Source: IITA-DTMA Field Survey, 2015