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PRODUCTIVITY AND EFFICIENCY ANALYSIS OF INTEGRATED PEST MANAGEMENT TECHNOLOGY ADOPTION AMONG MAIZE FARMERS IN SOUTHWEST, NIGERIA

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ABSTRACT

The objective of the study was to investigate the productivity and efficiency effect of Integrated Pest Management Technology Adoption among Maize Farmers in Southwest, Nigeria. The research estimated the technical efficiency, allocative efficiency and economic efficiency; also examined the effects IPM adoption on maize productivity. Multistage random sampling technique was used to select a total of two hundred farmers from whom primary data were collected using a structured questionnaire. The data collected were analyzed using descriptive statistics, stochastic frontier function and instrumentation, Stochastic frontier production function estimates showed that the mean technical efficiency is 80.16% for all respondents. The allocative efficiency of the land rent was 0.188 and was significant at 1 percent, the mean allocative efficiency was 106.8% and the mean economic efficiency was 85.7% for adopting IPM by maize farmers in the study area. The LATE estimate was carried out for the outcome (productivity). The Average Treatment Effect (ATE) in the entire population was 239.54 kg/ha, the ATEI on the sub-population of adopters was 267.34. This implies that the adopters had an increase of 267.34 kg/ha in maize productivity. Also, the LATE estimates suggest that the adoption of Integrated Pest Management Techniques significantly increases maize productivity by 318.29 kg/ha. This could be interpreted as the change in maize productivity that is attributed to a change in improved agricultural technology.

Keywords: Productivity, Efficiency, Integrated, Pest Management Technology, Adoption and Maize Farmers

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INTRODUCTION

Maize (*Zea mays*) is an important food crop widely grown in the tropics. The crop forms the taple foods for most of the population especially in areas adaptable for its production (Ofor *et al*., 2009). Most rural farmer grow the crop either for food, cash or both (Ofor *et al*, 2009). However, profitability and productivity of the crop is low in developing countries which have been blamed for poverty among rural farmers as well as the world food problems (CIMMYT, 2011). The low profitability and productivity of the crop in those countries, Nigeria inclusive have been found to be less than those from developed countries owing to a number of factor suchas pests and diseases (Alimi, 2012), poor soil fertility and lack of inputs (Iken and Amusa, 2004) and poor resource use (Adeyemo and Akinola, 2010; Idumah and Okunmadewa, 2007; Tijani and Osotimehin, 2007).

Pests and diseases are the major causes of low output in maize which in turn result in poor productivity which has exacerbated poverty and food insecurity among maize enterprise operators (Tounou *et al*., 2013; Ofor *et al*., 2009; De Groote, 2002). Insect pests have been defined by Williams (1947) as any insect in the wrong place. Cereals especially maize are vulnerable to pests and disease attacks (Iken and Amusa, 2004 and Tounou *et al*., 2013). Iken and Amusa, (2004)) and Tounou *et al*. (2013) added that insect pests are the most critical pests of maize.

The major insect pest problems on maize in the field are the stem borers, (*Busseola fusca* and *Sesemia calamistis*); shoot flies (*Atherigona* spp); grasshoppers (*Zonocerus variegatus*) and army worms (*Spodoptera exempta* and *Helicoverpa armigera*). The damage by stem borer‘s attack is usually more severe in late maize than the early ones (Ofor *et al*., 2009). These insect pests feed inside the plant stems and cause two major damages which are: first, mechanical damage due to consistent feeding on the stem, weakening it, and thus rendering the stems susceptible to lodging called stem falling and withering (dead heart). Second, characteristic perforations or windows on leaves called fenestrations‘ seen when the sheath opens exposing the perforations (Ofor *et al*., 2009). These harmful activities of the insects have direct impacts on crop cultivation through a cascade of events linking injuries they inflict on crop stands, the losses in crop quantity and quality these injuries may cause, and the economic costs this damage may generate (IITA, 2010; USAID, 2010).

The amount of damages and losses depends on the nature of the crop, the nature of the harmful organisms, and the production situations, as well as on climatic conditions favoring pest outbreaks and damage (Mihm, 1997). first, there is lost harvest, but then there are wasted resources invested in the crop, including water, fertilizer, seeds, labor, and energy. Second, often hidden component of croplosses, pests have a very serious bearing on the sustainability of both agricultural systems and food security (Mihm, 1997). Farmers‘ needs to boost enterprise yield and profitability as well as food security while fighting insect pests and yield-limiting crop pathogens below the economic injury level have led to the farmers‘ adoption of synthetic pesticides (Schwab *et al*., 1995 The development and appearance of new weeds and increase in insect pests and diseases have increased over the years which have made the traditional Nigerian farmers heavily rely on pesticides use for the control of various weeds, insect pests and diseases, resulting to the high importation of these products and their prices have become so high that it is becoming impossible for local farmers to afford (Nwanze, 1991; Oruonye and Okrikata, 2010).

The use of synthetic pesticides is not without negative impacts. The recognized negative impacts include environmental contamination and destruction of the ecosystem, resistance of pests to pesticides and health problem associated with the chemical‘s residue on crop produce. Addressing the negative economic and environmental impacts of pesticides

application as well as ensuring sustainable maize production for the purposes of better profit, yield, food security and better livelihood among the maize farm families, smallholder farmers have been charged with the use of alternative pests control methods called the integrated pest management (IPM) technology. Integrated pest management (IPM) is defined as a sustainable approach to managing pests by combining biological, cultural, physical and/or chemical tools in a way that minimizes economic, health and environmental risks. Despite the recognized positive impacts of IPM technologies on farms' productivity and profitability and hence poverty and food security, smallholder maize farmers' adoption of the beneficial technologies in the area is low (Kamara, 2013). The low adoption rate has been traced to factors such as socio-economic and institutional characteristics. Pests are factors responsible for significant losses which emanate from the various damages that are estimated to vary from 26 to 40 % of the attainable yield in major food and cash crops, including maize (Kamara *et al.,* 2009). These losses have been a major source of concern to farmers, government, non-governmental and international organisations. Pests have a very serious bearing on the sustainability of both agricultural systems and food security.

Addressing the problems of maize damage caused by insect pests, farmers have adopted conventional methods of control. The conventional methods involves the application of chemicals which has increased cost of production, contaminate produce, threaten the ecosystem, impair human health and hence reduced farmers' net returns with attendant poverty. To alleviate these problems, several IPM technologies were developed and introduced to the farmers. IPM is a pest management technology that emphasised the reduced or total non-use of synthetic chemicals in the control of pests and diseases for the purposes of enhancing farms' yield and profit while aspiring a healthy environment (IITA, 2010). Despite the established potential positive benefits of the technology on both the yield, the adoption rate in Nigeria is still very low (Kamara, 2013).

Farmers' risks attitude plays prominent roles in technology choice. Farmers are however known to be risk averse and hence analysis of technology adoption must take into account the risk attitudes of the farmers. These may contribute to farmers' unwillingness to use a new technology or abandon the conventional method. It becomes imperative to investigate the determinants of abandonment of pesticides, IPM use decisions and effects on net returns, yield, poverty and food security.

Crop losses amount to a double penalty on farmers, communities, consumers, and societies in the following ways, first, there is lost harvest, second, often hidden component of crop losses, pests have a very serious bearing on the sustainability of both agricultural systems and food security (Mihm, 1997). The use of synthetic or chemical pesticides is not without negative impacts. The potential negative impacts of this chemical usage practices have long been recognized. The recognized negative impacts of this practice include environmental contamination and destruction of the ecosystem, high cost of pesticides, resistance of pests to pesticides and health problem associated with the chemical's residue on crop produce (Samiee *et al*., 2009; Tijani, 2006; and Ofuoku *et al*., 2008). Pesticides reduce or eliminate pests and hence effectively increase yields but decreases net returns and diminish water and soil quality (Mauceri, 2004). This research will therefore determine the productivity impact of adoption of integrated pest management technology.

Research objectives: The objective of the research was to determine the efficiency and productivity effects of integrated pest management techniques' adoption among Maize farmers in Southwest, Nigeria.

LITERATURE REVIEW

Maize production in Nigeria

Maize constitutes an important cereal food crop in SSA with over 50% of all countries allocating over 50% of their cereal crop production area to maize (Bamire *et al*. 2010). More than 650 million people in this part of the world consume an average 43 kg of maize/year (FAOSTAT, 2006). In Nigeria, for instance, maize is one of the two major crops that occupy about 40% of the land area under agricultural production, and accounts for about 43% of the maize grown in West Africa (Smith *et al*. 1997; Phillip, 2001; Kamara *et al*., 2009; Bamire *et al*., 2010). An area of 20.7 million hectares is planted to maize in the whole of the African continent, with an average annual production of 29 million tons which is expected to be doubled in the next decade due to expansion of area of cultivation (Christopher *et al*., 1996). In SSA, three quarters of the total production of maize is consumed as human food, which is also the case with other cereals such as sorghum and millet. Maize production has over the years spread all over the country due to the development of short season early maturing varieties, where the growing period is 90–100 days (Fakoreded *et al*, 2003). Despite the expansion in these production areas, maize yields in farmers‘ fields average from 1 to 2 t/ha in contrast to the higher yields of about 5 to 7 t/ha reported on breeding stations in the region (Fakorede *et al*. 2003; Kamara *et al*., 2008; Kamara, 2013). Several factors are responsible for this considerably low level of yield, of which insect pests are chiefly involved. In the Kenyan highlands, total losses due to pests in maize were estimated

Crop losses to insect pests

Small scale grain production is essential for the growing population of Africa and Nigeria, inclusive. An area of 20.7 million hectares is planted to maize in the whole of the African continent, with an average annual production of 29 million tons (Christopher *et al*., 1996; Kamara *et al*., 2005).Weeds and insects constitute major threats to crops‘ productivity by directly damaging crops and cause yield losses in many ways such as either eating the plant‘s part directly or inflicting injuries on the plant (Ekeleme *et al*., 2008). While weeds compete with crops for nutrients, air and space, and may parasitize or contaminate crop seeds, insects eat plant leaves and make them unattractive thereby causing serious damages on crops. Insects are the most diverse species of animals living on earth and are undoubtedly the most adaptable form of life as their total numbers far exceed that of any other animal category (FAO, 2001). Insects’ damages are at increasing rate because every stage of insets, life cycle is injurious to plants (FAO, 2001).

Pesticides use in maize production in Nigeria

Insect pests, such as stem borers, armyworms, silkworms, grasshoppers, termites and weevils affect the yield of the crop and hence it profitability. Effective control of these pests and diseases require the use of chemical agents called pesticides (Tijani and Sofoluwe, 2012). According to them, chemical substance called pesticide include insecticides and fungicides. Use of chemicals (insecticides) is presently the most popular control measure in Nigeria (Daramola, 1991; Tijani and Sofoluwe, 2012). Insecticides are the quickest and most pragmatic means of combating an infestation, but their uses have been restricted in many parts of Africa because of cost and their ability to contaminate the environment, leaving harmful residue in produce and induce resistance in pest species (Lale, 2002; Owusu, 2007; Dahiru *et al*., 2013).

Integrated Pest Management efforts in Nigeria

Increase in pesticides uses for pests control is harmful to both the environment and public health. In order to reduce the incidences of pests as well as ensures public health in Nigeria, a number of project based interventions have been carried including those funded by the World Bank and FAO on IPM as well as the establishment of ministries and agencies that will make it work. There are also other IPM implementation cases amongst the key crops in Nigeria, for example, in the control of root knot nematodes in tomato and okra, farmers are encourage to integrate resistant crop varieties with seed dressing and compatible crop rotation schemes to prevent build up of the pests. For downy mildew control in maize, farmers were encouraged to promote the integration of resistant crop varieties with seed dressing (using Apron plus), timely identification, rogueing and burning of affected plants and general farm hygiene. Similarly, IPM recommendations for control of the African Rice Gall Midge include combination of resistant crop varieties with seed dressing, timely planting, pest monitoring to guide pesticide applications.

RESEARCH METHODOLOGY

Area of Study

The study was carried out in the Southwest, Nigeria. Nigeria lies between longitude 2^0 42' and 6^0 03'East of Greenwich and latitude 5^0 49' and 9^0 17' North of the equator (Balogun, 2003). The Southwest comprises Osun, Ogun, Ondo, Ekiti, Oyo, and Lagos States. Three states are selected (Ekiti, Ogun and Osun) based on their prominence in the use of integrated pest management technology The Southwestern Nigeria is bounded in the North by Kwara and Kogi States and in the East by Edo State. In the West, the study area is bounded by Republic of Benin and in the South by the Atlantic Ocean. The four main vegetation belts in Southwestern Nigeria are the swamp on the Atlantic coast, tropical rainforest and the derived savannah in the middle, and Guinea savannah in the North.

The study area enjoys a bi-modal rainy season which lasts from April to October and a dry season from December to March (mean annual rainfall of 135mm and mean daily temperature of 35^0C (BBC Weather Centre, 2008). The total population of the six states according to the 2006 National Census is 27,722,427 (NPC, 2007), while the total land mass of the study is 67,174.6 km^2. Majority of the inhabitants are predominantly small holder farmers who depend on agriculture for their livelihood. The prevailing vegetation, soil, and weather conditions determine the type of crops grown in different areas of southwest Nigeria. The main permanent crops cultivated in the study area are oil palm, cocoa, kolanut, and cashew, while food crops grown include maize, rice, cassava and yam, pineapple, banana and plantain. Maize is however becoming an important food crop in the area. The people live mostly in organized settlements, towns and cities.

Sampling Procedure

A multi-stage sampling procedure was employed for the selection of respondents for the study. In the first stage, purposive sampling technique was used to select three states Ekiti, Ogun and Osun states based on their predominance in the use of Integrated Pest Management Southwestern Nigeria. In the second stage, four LGAs per state and three villages per LGA were purposively selected based on the prominent use of Integrated Pest Management. In the third stage, 10 adopters and 10 non-adopters of Integrated Pest Management were randomly selected in each village to give a total of six hundred maize farmers for the study.

Quantitative and qualitative data were used for the study. Quantitative data will be collected with the aid of structured questionnaire. Data were collected on the socio-economic characteristics such as age, level of education, farm size, credit access, off-farm income etc; institutional factors such as membership of association, extension contact, membership of cooperative etc as well as the input-output data the respondents. Data were collected on the pest control methods used, methods combined, awareness and compliance level of IPM practices, adoption and the level of adoption of IPM practices as well as the perceived effectivity of the practice. Qualitative data were collected with the aid of Focus Group Discussion (FGD). This was done conducted to measure the awareness, perception, adoption level, potential benefit and extent of IPM in the study area.

Analytical techniques

Descriptive statistics

Descriptive statistics involving the use of mean, percentages and standard deviation was to investigate the adoption typology, socio-economic characteristics of farm households and summary statistics of the other variables of importance. This method of analysis describes the basic features of the data in a study. Descriptive analysis does, however often provide guidance for more advanced quantitative analyses (Bobabana and Wabbi, 2011).

Production function

The production function was used to compute the moments of production that was employed in analysing the determinants of farm technology adoption in the study area. The econometric estimation of production risk impact on IPM technology adoption was conducted in two steps. In the first step, three sample moments (namely, mean, variance, and skewness) of each household from the production function was computed. These moments was included alongside other explanatory variables in the triple hurdle model, in order to determine if production risk has any impact on farm technology adoption (Juma *et al*., 2009). In achieving this, maize production per unit area was regressed on farm inputs, including IPM inputs, observed plot, and household and institutional characteristics to get the estimates of the mean effect.

The model is specified as follows: where Y is the maize output per unit of land obtained by the household under each IPM typology; L and X are production inputs/technologies, ε is the random variable denoting unobserved variables, β is a vector of parameters to be estimated, and H refers to the household endowments. The i_{th} central moment of value of maize production about its mean is given as: where μ denotes the mean value of maize production. The estimated residual from the mean regression are estimates of the first moment of value of maize production distribution. The estimated residuals ε was then squared and regressed on the same set of explanatory variables as in equation. Propensity score matching and Local Average Treatment Effect (LATE) model were used to measure the productivity impact.

Stochastic Frontier Production Function (SFPF)

The stochastic frontier production model was used to determine the technical, allocative and economic efficiencies of farmers and to analyse the factors influencing their level of efficiency. The stochastic frontier production model was independently specified by Aigner, Lovell and Schmidt (1977) and Meeusen and Van den Broeck (1977). It comprises a production function of the basic regression type with a composite disturbance term equal to the sum of the two error components.

The basic model used in literature to describe a frontier production function is specified as follows:

$Y_{i=}f(W_i;\beta_i) + V_i - U_i$.....(1)

Where $Y_{i=}$ Maize output measured in kg/ha, X_i are explanatory variables and V_i and U_i are the error terms

It is further assumed that V and U are not correlated.

For this study, the translog variant of the model used is specified as:

$In\ Y_{i=}\ In\ \beta_0 + \sum\beta_i InX_i + V_i - U_i$.....(2)

Where,

ln = the natural logarithm (i.e., logs to base e);
Y_i = total quantity of maize output of the i-th farm (kg/ha);
W_i = farm size (ha) or total land planted to maize crop (ha);
W_2 = labour (mandays);
W_3 = total quantity of fertilizer (kg);
W_4 = amount of other agro-chemical inputs (herbicides, pesticides etc) in naira;
W_5 = Use of IPM
$\beta_0,\beta_1,\beta_2,\beta_3,\beta_4,\ldots.\ \beta_5$ = Vectors of unknown parameters to be estimated

V_i = random error assumed to be independent of U_i, identical and normally distributed with zero mean and constant variance $N(O\sigma v^2)$. They represent random variations in output as a result of factors outside the control of farmers as well as the effects of measurement error in output variable.

V_i = random variables that accounts for technical inefficiency effects which are assumed to be independent of V_i non-negative truncation at zero or half normal distribution with $N(O\sigma v^2)$.
i = 1,2,3… n farms

The model to be used for allocative efficiency is specified as:

$In\ C_i = \delta_0 + \delta_1 In\ W_i + \delta_2 In\ W_2 + \delta_3 In\ W_3 + \delta_4 In\ W_4 + \delta_5 In\ Y_6 + (V_i + U_i)$ .....(3)

Where,
i refer to the i-th sample farm
δ_0 = allocative efficiency level;
C_i = total cost of production (₦/ha)
W_i = cost of labour (₦/ha)
W_2 = cost of seeds (₦/kg)
W_3 = cost of fertilizer (₦/kg)
W_4 = cost of other agro-chemical inputs (herbicides, pesticide etc) (₦)
Y_5 = Quantity of maize produced (kg/ha)
V_i and U_i are as earlier defined; and $\delta_1,\delta_2,\delta_3\delta_4$ and δ_5 = vectors of unknown parameters.

Allocative efficiency of individual farmers is defined in terms of the predicted minimum cost (C_i^*) to observed cost (C_i) (Ogundari and Ojo, 2007; Okoruwa *et al*., 2014) is specified as: $AE = C_i^*/ C_i = \exp(U_i)$ .....(4)

AEi = is the allocative efficiency of the i-th farm, C_i represents the actual total production cost while the minimum cost (C_i^*) represents the least total production cost.

The a prior expectation is that all the independent variables (W_i – W_5) should have a positive relationship with the total variable cost.

Economic efficiency was obtained through the identity

$EE_i = TE_i x AE_i$

EE_i = Economic Efficiency of i – th farm

TE_i = Technical Efficiency of i – th farm

AE_i = Allocative Efficiency of i – th farm.

Impact Assessment Techniques: Two techniques were used to analyse the impact of IPM on productivity and efficiency of production. These are the Propensity Score Matching and Instrumental variable regression.

Propensity Score Matching Method (PSM): The propensity score matching method was used to analyse the impact of IPM adoption on Maize productivity and efficiency of production by the farming households. Similar studies such as Awotide (2012) have used propensity score matching to evaluate productivity impact of technology adoption. Propensity score matching (PSM) method is a quasi-experimental approach that controls for the self-selection that normally arises when technology adoption is not randomly assigned and self-selection into adoption occurs.

In experimental studies referred to as randomized control trials (RCTs), this problem is addressed by randomly assigning adoption to treatment and control status, which assures that the outcome variables observed on the control households without adoption are statistically representative of what would have occurred without adoption. However, in quasi-experimental approaches, adoption is not randomly distributed to the two groups of the households, but rather the household itself deciding to adopt given the information it has. The main parameter of interest in a non-experimental framework is the average treatment effect for the treated population (ATT), expressed as:

$$\tau ATT = E(Y_i - Y_0 \mid D = 1) = E(Y_i \mid D = 1) - E(Y_0 \mid D = 1) \quad \text{.....(26)}$$

Where Y_1 denotes the value of the outcome of adopters of improved rice variety (1), and Y_0 is the value of the same variable for the non-adopters (0). The problem that arises with unobservability is by virtue of the fact that $E(Y_i \mid D = 1)$ can be estimated but not $E(Y_0 \mid D = 1)$. Although $\tau = E(Y_i \mid D = 1) - E(Y_0 \mid D = 0)$ can normally be estimated, it is potentially a biased estimator of τATT. This kind of bias is a central concern in non-experimental studies (Smith and Todd, 2005).

Rosenbaum and Rubin (1983, 1985) suggest using the propensity score matching (PSM) model to account for sample selection bias that results due to observable differences between treatment and comparison groups (Dehejia and Wahba, 2002). PSM controls for self-selection by creating the counterfactual for the group of adopters.

PSM constructs a statistical comparison group by matching every individual observation on adopters with individual observations from the group of non-adopters with similar characteristics. In effect, the matching procedure creates the conditions of a randomised experiment in order to evaluate a causal effect, as in a controlled experiment (Rosenbaum and Rubin, 1983). To achieve this, the matching approach employs the conditional independence assumption (CIA), which states that technology selection is random and uncorrelated with the outcome variables, once one has controlled for Z.

PSM estimates will be reliable, provided participants and controls have the same distribution of unobserved characteristics. The failure of this condition to hold is often referred to as a problem of "selection bias" in econometric, or "selection on unobservables" (Heckman and Robb, 1985). Secondly, the support for the comparison and the program participants should be the same. Finally, it is desirable that the same questionnaire is administered to both groups and that participants and controls be derived from the same economic environment.

The CIA or "strong unconfoundedness" can be given as:

$$Y_i, Y_0 \text{ II } D \mid Z$$

The effect of adoption on the outcome variables can then be expressed as:

$$\text{ATT}(z) = (Y_i - Y_0) \mid z)$$
$$= E (Y_i \mid D = 1, Z) - E (Y_0 \mid D = 0, Z)$$

The average adoption effect can then be represented as:

$$= E \{(z)\}$$

Under the condition of random technology adoption, outcomes for similar households with different adoption statuses can be compared (i.e. adopters vs. Non-adopters), with similar households being defined according to the values of Z. The propensity score reduces the dimensionality of the conditioning problem associated with Z by comparing households with similar probabilities of adopting the new technology, given the relevant controls of Z (Dehejia and Wahba, 2002). The conditional probability of adopting the new technology, given the control of *Z*, is as follows:

$$P(Z) \equiv P (D = 1 \mid Z) = E (D \mid Z)\ldots$$

Where D = {0, 1} is the indicator of exposure to treatment and *Z* is the multidimensional vector of pre-treatment characteristics. As indicated above, the propensity score is a function such that the conditional distribution of *Z*, given *p* (*Z*) is the same in both groups, namely is conditional to *p* (*Z*), *Z* and *D* are independent. This balancing property of the propensity score can be expressed as $DZ \mid p (Z)$ (Lee, 2008).

Hence, if the unconfoundedness assumption holds, all biases due to observable components can be removed by conditioning on the propensity score (Imbens, 2004). Given the propensity score, which can be estimated by any standard probability model, the ATT can be estimated under the CIA as follows (Becker and Ichino, 2002):

$$\text{ATT} = E\{Y_i - Y_0 \mid D = 1\}$$
$$\{E\{ Y_i - Y_0 \mid D = 1, p(Z)\}\}$$
$$=E\{E\{ Y_i \mid D = 1, p (Z)\}$$
$$- E \{Y_0 \mid D = 0, p (Z)\} \mid D = 1\}$$

Another important requirement in conducting the matching method is the common support condition (CSC). Heckman *et al.,* (1997) point that it is only in the overlapping subset of the comparison and treatment groups that comparable observations can be matched. The overlap condition is defined as follows:

$$0 < (D = 1 \mid Z) < 1$$

By the overlap condition, the propensity score is bounded away from 0 and 1, excluding the tails of the distribution of *p* (Z). This assumption ensures that persons with the same values have a positive probability of being both adopters and non-adopters. If there are regions where the support of Z does not overlap for the different groups, matching is only justified

when performed over the common support region. A violation of the CSC is a major source of bias due to comparing incomparable individuals (Heckman *et al.,* 1997).

Individuals that fall outside the region of common support have to be discarded and so the treatment effect cannot be estimated. Having estimated the propensity scores, the next stage involves matching the adopters with non-adopters with similar propensity scores. Several techniques have been suggested in the literature to find the "closest" neighbour as a matching partner.

Five approaches are commonly used to match treatment and control groups. Although all of the approaches should normally yield the same results asymptotically, the choice of a matching approach could become important when using small samples (Heckman *et al.*, 1997). These approaches include nearest-neighbour matching, stratified matching and radius matching. These are all based on the propensity score. Nearest-neighbour matching simply identifies each household's "closest twin" in the opposite adoption status; then it computes an estimate of the technological effect as the average difference of the households' outcome between each pair of "matched households".

The kernel-based matching estimator is more flexible than the former with respect to the specification of the propensity score. It follows the same steps as the nearest-neighbour method. However, the "matched household" is identified as the weighted average of all households in the opposite technological status within a certain propensity score distance, with weights being inversely proportional to the distance. More specifically, the ATT is the difference between two terms with the first term being the outcome indicator for the adopters which is observable and the second term being the outcome indicator for the adopters had it not been treated, representing a counterfactual situation which is unobservable and needs to be treated.

Propensity score matching tries to compare the differences between the outcome variables of adopters and non-adopters with similar inherent characteristics. It cannot correct unobservable bias or endogeneity because propensity score matching only controls for observed variables (to the extent that they are perfectly measured) (Amare *et al.*, 2012).

Therefore, in this study, propensity score matching (PSM) estimates is complemented with instrumental variables (IV) method, another quasi-experimental approach, generally applied by economists working with cross sectional data (Yorobe and Smale, 2012).

Instrumental Variable (IV) Regression Method

Instrumental variable is an important quasi-experimental technique with numerous applications in agriculture. Ivs allows us to get unbiased estimate of causal effect even when there is selection bias, unobserved confounding or imperfect complaince. Although PSM technique controls for biases due to observed characteristics, it still cannot correct biases due to unobserved characteristics or endogeneity. For example, some maize farmers may be more motivated to adopt than others, and this may cause them to be adopters of IPM .the degree of this motivation or dynamism is not observable, but it can still bias estimates obtained through PSM technique. The problem of endogeneity might also arise from criteria used for program placement and this is typically not a random process. This clearly leads to issue of such endogeneity bias and a possible estimation strategy to control for it is needed.

RESULTS AND DISCUSSION

Technical, allocative and economic efficiencies of IPM Maize farmers

Table 1: Technical efficiency scores of respondents

Efficiency	Frequency	Percentage
< 30%	1	0.5
31% - 50%	1	0.5
51% - 70%	23	11.5
71% - 90%	159	79.5
>= 91%	16	8.0
Total	200	100.0

Minimum: 0.115
Maximum: 0.950
Mean: 0.802
Std. deviation: 0.103
Source: Data Analysis, 2026

Allocative efficiency of respondents

Table 1 show the estimated level of allocative efficiencies of IPM Maize farmers in the study area. The minimum allocative efficiency score was 1.013 and the maximum efficiency score was 1.66 with a mean efficiency of 1.068. About 95% of the total respondents were between 1.01 and 1.2 level of efficiency score, 3.5% were between 1.21 and 1.4 efficiency levels. 0.5% was above 1.61 efficiency score.

This indicates that the farmers were not efficient in their allocation of resources for Maize production as their efficiency score is greater than 1. This variation from allocative efficiency frontier (1) is an indication that all of the farmers allocate their resources inefficiently in their production process. This result suggests that the farmers were not minimizing production costs, indicating that they were utilizing the inputs in the wrong proportions, given the input prices.

This corroborates the study by Asogwa et al. (2011) on efficiency of small scale farmers in Nigeria, that their minimum allocative efficiency is greater than one (1.05) with the mean of 1.88, suggesting that farmers were utilizing the inputs in the wrong proportions, at the given input prices.

Table 19: Allocative efficiency scores of respondents

Efficiency	Frequency	Percentage
<= 1	0	0
1.01 - 1.2	190	95.0
1.21 - 1.4	7	3.5
1.41 - 1.6	2	1.0
>= 1.61	1	0.5
Total	200	100.0

Minimum: 1.013
Maximum: 1.66
Mean: 1.0681
Std. deviation: 0.866
Source: Data Analysis, 2015

Economic efficiency levels of respondent

Table 2 shows that the calculated economic efficiencies for all the respondents ranged from 0.112 for the least efficient farmer to 1.465 for the farmer that attained the highest efficiency score, with mean of 0.857. Also, majority (54.5%) of respondents had between 0.71 and 0.90 efficiency score, 37% had above 0.90, 7.5% had between 0.51 and 0.70 efficiency score, only 0.5% efficiency score below 0.30. This result shows that IPM Maize farmers had high level of economic efficiency, though there is still room for improvement of the mean efficiency by 0.143. The wide variation in economic efficiency estimates is an indication that some of the farmers are still economically inefficient in the use of resources for production and there still exists opportunities for improving on their current level of economic efficiency. This result suggests that some of the farmers in the study area were not maximizing profit. This result is in agreement with studies carried out by Asogwa et al. (2011), Ambali et al. (2012) and Ogunniyi (2015) on economics efficiency that overall economic efficiency could be improved upon by optimum utilization of resources at the given input price in order to maximize profit.

Table 2: Economic efficiency scores of respondents

Efficiency	Frequency	Percentage
<= 30%	1	0.5
31% - 50%	1	0.5
51% - 70%	15	7.5
71% - 90%	109	54.5
>= 91%	74	37
Total	200	100

Minimum: 0.122
Maximum: 1.465
Mean: 0.857
Std. deviation: 0.135
Source: Data Analysis, 2015

Productivity Impact of Integrated Pest Management Techniques' Adoption

Due to the problem of selection bias and particularly non-compliance or problem of endogenity, this study uses a combination of methods to access the impact. The impact of IPM on Maize productivity was estimated by the use of Average Treatment Effect using propensity score matching techniques and Local Average Treatment Effect (LATE) model for the purpose of comparism. The LATE estimate was carried out for the outcome (productivity). The result of the impact of Integrated Pest Management Techniques is presented. The Average Treatment Effect (ATE) in the entire population was 239.54 kg/ha, the ATEI on the sub-population of adopters was 267.34. This implies that the adopters had an increase of 267.34 kg/ha in Maize productivity. Also, the LATE estimates suggest that the adoption of Integrated Pest Management Techniques' significantly increases maize productivity by 318.29 kg/ha. This could be interpreted as the change in maize productivity that is attributed to a change in improved agricultural technology.

TABLE 3

Estimation of Integrated Pest Management Techniques' adoption on Maize output

Estimation methods	Parameters	Std. Error
Propensity score matching	-	-
Average Treatment Effect (ATE)	239.54*	123.00
Average Treatment Effect (Adopters) (ATE1)	267.34*	107.16
Average Treatment Effect (Non-adopters) ATE0	210.93*	136.29
Local Average Treatment Effect		
LATE	318.29*	117.22

Source: Data analysis, 2025
*significant at 5% alpha level

Conclusion and recommendations

Based on the conclusion, the following suggestions are made:
(i) There should be creation of more Innovation platforms and that farmers should be encouraged to participate in the use of IPM so as to unleash the potentials in IPM as a means of improving maize production.

(ii) IPM Maize farmers should be guided through effective training and enlightenment programmes of extension services to allocate their limited resources appropriately for efficient production.

(iii) There should be incentives for more youth and women to be actively involved in the adoption programmes of IPM for more efficient production of Maize

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