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EFFECTS OF INTEGRATED PEST MANAGEMENT TECHNOLOGY ON FOOD SECURITY OF MAIZE FARMING HOUSEHOLDS IN NIGERIA

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Abstract
In enhancing sustainable crop production through the adoption of eco-friendly pest management practice, integrated pest management (IPM) practice was introduced to crop farmers, including maize farmers, in Nigeria. The study therefore, used cross-sectional data collected from 400 maize farming households to investigate the effects of IPM on household food security. We determine the effect of IPM on households' food security using Instrumental Variables (IVs) while endogeneity was corrected for. Results of analysis revealed that IPM adoption was influenced by education of household head (p≤0.1) and extension access (p≤0.05). Findings further showed that IPM had positive and significant effect on household food security in terms of calorie and protein intake as well as food expenditure. Therefore, maize farmers in the study area should be encouraged to adopt IPM for the purpose of raising household food security.

Key Words: *Maize, Integrated pest management, Instrumental Variables, Food security*

Introduction

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*., 2013). 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 (Bamire *et al*., 2013).

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 (Fakorede *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 (Kamara, 2013).

Several factors are responsible for this considerably low level of yield, of which insect pests are chiefly involved. In Nigeria, insect pests account for about 46% loss in maize (IITA, 2010). The high loss in maize has threatened food security among the farming households as well as predisposed them to poverty.

Farmers' needs to boost enterprise yield as a means of ensuring food security and improving the country's GDP through grains farming while fighting insect pests and yield-limiting crop pathogens had led to the introduction of Integrated Pest Management Technology (IPM) by the federal Ministry of Agriculture through the Integrated Pest Management Plan (IPMP) in the Third Fadama Project (Federal Ministry of Agriculture and Rural Development (2013). The programme was implemented to reduce the over 125,000 metric tons of pesticides applied in Nigeria while aspiring optima yield of maize for food security among the farming households (Federal Ministry of Agriculture and Rural Development, 2013). IPM is a broad ecological approach which aims at keeping pest population below economic threshold level by combining more than one method of pest control such as, cultural, mechanical, biological, chemical and legislative in a compatible and environmentally compliant manner while aspiring maximum and continuous profit (Samiee *et al*., 2009).

Studies by Ofuoku *et al*. (2008) and Samiee *et al*. (2000) investigated factors influencing adoption of IPM technology without concern on the impact of the technology on households' welfare while Isoto *et al*. (2014) estimated the impact of IPM technology on farmers' revenue. However, no known published studies in Africa had estimated the impact of IPM on household food security, hence the study.

Research Methodology

Area of Study

The study was conducted in Edo and Delta States, Nigeria. The states are located in the South-Southern, Nigeria. The climate of the region varies from the hot equatorial forest type in the southern lowlands to the humid tropical in the northern highlands. The wet season is relatively long, lasting between seven and eight months of the year, from the months of March to October. The mean annual rainfall ranges from over 4,000mm to 3,000mm in the region. Temperatures are generally high in the region and fairly constant throughout the year. Average monthly maximum and minimum temperatures vary from 28^oC to 33^oC and 21^oC to 23^oC, respectively, increasing northward and westward. Farmers in the area grow both tree and arable crops. The major trees crops grown are oil palm, rubber, coconut etc while the major arable crops grown are maize, cassava, groundnut, etc. Historically, farmers in the region have adopted various cultural practices compatible with the environment regimes and human health in the control of maize pests and diseases. The total land area in the area is 86km^2. The map of the study area is shown in Fig. 1.

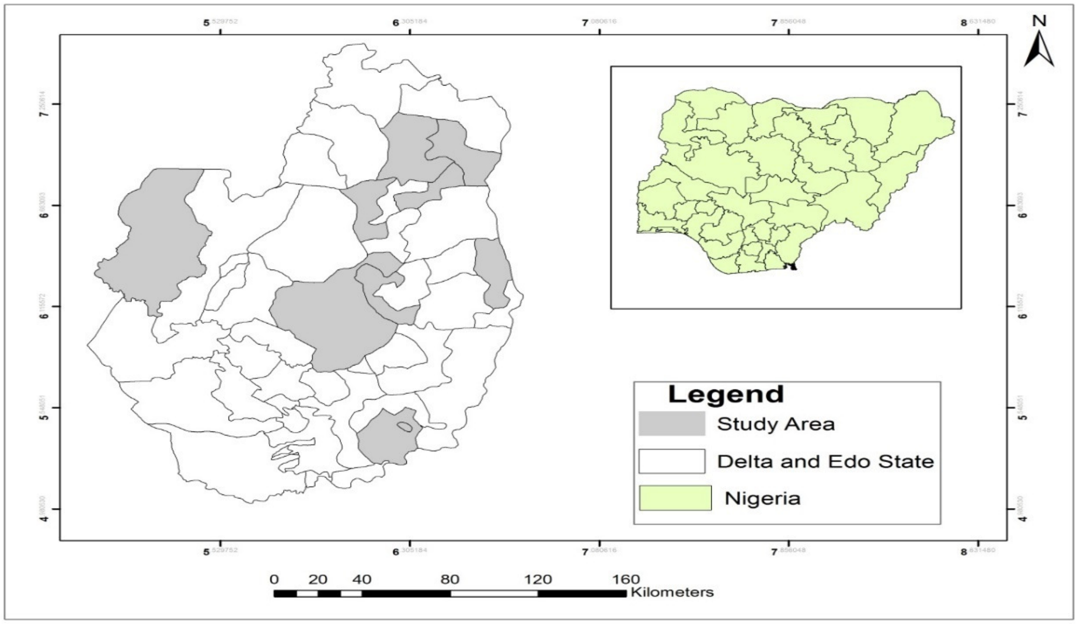

Fig. 1: Map of the study area

Sampling Techniques, Sample and Data

Multistage sampling procedure was used for the study. In the first stage, three and two agro-ecological zones (AEZs) were purposively selected in Edo and Delta States, based on involvement in maize production. In the second stage, two Local Government Areas (LGAs) per AEZ were randomly selected. In the third stage, two villages per LGA were sampled using simple random technique. In the final stage, 20 maize farmers per village were sampled. A total of 400 respondents were sampled in all for the study. Primary data were collected for the study with the aid of structured questionnaire. Data were collected on socio-economic characteristics such as age, level of education, farm size, credit access and off-farm income; institutional factors such as membership of association, extension contact, membership of cooperatives, as well as the input-output data of the respondents. Data were also collected on the pest management methods used. Data collected were analysed with the aid of descriptive and inferential statistics as well as econometric models.

Empirical Framework

In estimating the effects of integrated pest management technology on food security of maize farming households in the study, the authors follow Asante *et al*. (2014), where farmers' adoption is modeled as decision variable and its determinants were estimated. The estimated predicted probabilities of adoption and other variables (household, farm-level and institutional) were regressed on the food security indices of the households measured by calorie intake, protein consumption and food expenditure. This was conducted with the aid of Instrumental Variables (IVs). Calorie/protein consumption as well as food expenditure were used as proxies for measuring food security. Calories/protein consumption/food expenditure model was specified and estimated for previous cropping season. Total calorie/protein consumption and food expenditure were used as dependent variable per capita per day. For better approximation into normal distribution, natural log of calorie/protein was taken. Consumption is made up of household's produced and purchased food - raw, boiled, roasted or fried. Technological change caused by IPM may influence food consumption through its effects on income stream.

Households' daily food consumption (Daily Calorie and protein intake) was obtained from household own food production and purchases to supplement own food production while food expenditure included all expenses on food consumed. The data on actual food consumed (crop and non-crop) by each household per week were obtained and converted to kilogram. The energy content of unit kg of each foodstuff (crop and non-crop) was obtained from literature as showed in Table 2. This approach corrects for endogeneity error and selection bias in adoption decision estimation before it consequence usage in food security effect estimation.

Table 2: Food stuff equivalent conversion ratios

Foodstuff	Calorie/kg
Wheat	3330
Rice	3590
Maize	3600
Sweet potatoes	970
Cassava	1090
Banana	750
Yam	900
Legumes average	2.6
Beef	6.25
Pork	6.25
Chicken	4.184
Leafy vegetable	3.87

Source: www.fao.org/docrep/x5557e/x5557e04.htm

The Probit Model for the Adoption Decision

The probit model uses the cumulative distribution function (CDF) to explain the behaviour of a dichotomous dependent variable. The probit model is suitable for analyzing adoption decisions that have dichotomous values (Given the assumption of normality, the probability that I_i* is less than or equal to Ii can be computed from the normal CDF as modeled below: $P_i = p(Y = 1/X) = p(I_i^* < I_i) = p(Z_i < \beta_1 + \beta_2 X_i) = f(\beta_i + \beta_2 X_i)$

Where

Where I* = critical or threshold level of the index, such that if Ii exceeds I*, the family will adopt, otherwise it will not. P (Y=1/X) is the probability that an event occurs given the values of X, or explanatory variable(s) and where Zi is the normal variable, that is, Z~N(0, Q2). The term "probit" was coined in the 1930s by Chester Bliss and stands for probability unit. These two analyses, logit and probit are the same. As discussed previously, probit uses the cumulative normal distribution. The probit model is defined as: Pr(y =1/X) = Φ (xb) Where Φ is the standard cumulative normal probability distribution and xb is called the probit score or index. Since xb has a normal distribution, probit coefficient is interpreted in the Z (normal quartile) metric. The interpretation of a probit coefficient is that one-unit increase in the predictor leads to increasing the probit score by b standard deviations. Learning to think and communicate in the Z metric takes practice and can be confusing to others. We will make use of a number of tools developed by Long and Freese to aid in the interpretation of the results.

The log- likelihood function for probit is:

$$lnL = \sum wjln\theta(xjb) + \sum wjln[1 - 0(xjb)]$$

Where wj denotes optional weights

The empirical form of the probit model is specified below:

$$P_i = \beta_0 + \beta_1 AGE + \beta_2 EDUHH + \beta_3 EDUSPOUSE + \beta_4 HHSIZE + \beta_5 FARMSZ + \beta_6 EXTNVISIT + \beta_7 FARMEXPR + \beta_8 PERCCOST + \varepsilon_i$$

Where

AGE = Age of household head (years)

EDUHH = Education of household head (years)

EDUSPOUSE = Education level of spouse (years)

HHSIZE = Household size

FARMSZ = Farm size

EXTNVISIT = Number of extension visits

FARMEXPR = Farming experience (years)

PERCCOST = Perceived cost of IPM (₦)

The IVs model employed in measuring the effects of IPM technology on the food security of maize farming households is modeled as follows:

$LNC_j = \theta m_j + \gamma Y_j + n_j$ and

$Y_j = \beta X_i + \mu_i$

Where C_j is the total daily per capital consumption of household *j* in Nigeria Naira, *mj*is a set of exogenous determinants that include household and community characteristics, *nj* is a random error term (Mukherjee and Benson, 2003). Y_i is the predicted values of *yi* from probit regression function in the OLS regression. The IVs used in this model were variables capable of influencing adoption but have no effects on the outcome variables.

Results and Discussion

Table 3 reveals the descriptive statistics of the maize farming households and test of means between the respondents' categories in the area. The results in the table revealed that a significant difference in the year of education of household head and number of extension visits ($p \leq 0.05$) between the respondents' categories.

Table 3: Descriptive statistics of maize farmers in the study area

Variable	Adopters (219)	Non-adopters (181)	T-test (p≤0.05)	Overall (400)
Age	48.8±11.0	50.5±12.4	2.014	49.7±11.8
Education of head	6±4.1	4±2.9	16.135**	5±3.5
Education of spouse	2±1.4	2±1.4	2.155	2±1.4
Extension	2±1.6	1±0.9	25.302**	1±1.3
Perceived cost of IPM	5±0.7	2±1.2		3±1.7
Household size	9±6.2	8±5.0	0.797	8±5.5
Farm size	3.1±2.0	3.3±2.0	0.868	3.2±2.0
Farming experience	18±59	18±6.3	0.484	18±6.1

Calorie and Protein Consumption and Consumption Expenditure

Table 4 revealed the households' calorie and protein intake and consumption expenditure. The daily food intake was computed by converting household food consumed into calorie and protein equivalents (Oguntona and Akinyele, 1992). The mean calorie consumption among the users of IPM was 2, 364.0 calories, while it was 1,514.4 calories among non-users. The users of IPM consumed more than the minimum calorie consumption of 2,250 kilocalories recommended per person compared to their non-users counterparts. The per capita daily protein intake was 32.8gm among the users of IPM while it was 26.2gm among non-users of IPM. The minimum recommended protein consumption per person per day was 35gm (Manyong and Houndekon, 1997). However, the daily per capita per day protein taken by the users of IPM was closer to the minimum 35gm per person recommended than their non-users counterpart.

The food expenditure included food purchased and produced by the households. The non-food expenditure included money spent on durable and non-durable households and farm items. The mean monthly food expenditures were ₦ 3,256.2 and ₦ 2,364.9, among users of IPM and non-users of IPM, respectively. However, the mean monthly expenditures on non-food items were ₦ 32, 145.2 and ₦ 25,362.4, among users of IPM and non-users, respectively. Users of IPM had more to spend on food and non-food expenditure on monthly basis than their non-users counterparts. The higher expenditure spent by the users of IPM could be traced to additional income from better yield and savings from pesticides expenses as well as the improved yield obtained from the use of the practice. The t-test statistics revealed significant difference in the means of per capita per day calorie ($p \leq 0.01$), total expenditure ($p \leq 0.01$), food expenditure ($p \leq 0.01$) and non-food expenditure ($p \leq 0.01$) between the users of IPM and non-users of IPM in the study area.

Table 4: Calorie and protein consumption and consumption expenditure

Item	Non-users of IPM	Users of IPM	t-test
Per capita per day calorie (kcal)	1,514.4	2, 364.4	5.4***
Per capita per day protein (gm)	26.2	32.8	1.3
Total expenditure (₦)	27,727.3	35,401.4	11.2***
Food expenditure (₦)	2,364.9	3,256.2	10.6***
Non-food expenditure (₦)	25,362.4	32,145.2	4.8***

Probit Model Results for IPM adoption in Nigeria

The Maximum likelihood estimates for parameters of the probit model for IPM adoption technology adoption in Nigeria is presented in Table 5. The results in the table revealed that education of household head, number of extension visits and household size were positive determinants of IPM technology adoption in the study area. Education of household head, number of extension visits and household size were significant at 10%, 5% and 10%, alpha levels, respectively. The estimated marginal effects revealed that an increase in the level of education of household head by 1 would increase probability of adoption by 2.1%. An increase in the number of contacts with the extension by a unit would increase the probability of adoption by 12.15% while an increase in household size by a unit would increase probability of adoption by 1.43%.

Table 5: Maximum likelihood estimates for parameters of the probit model for IPM adoption in Nigeria

Variable	Coefficients	mfx	SE	p-value
Constant	0.6301		1.0996	0.567
Age	-0.0328***	-0.0078	0.0126	0.009
Education of head	0.0879*	0.0210	0.0472	0.062
Education of spouse	-0.1399	-0.0333	0.1229	0.255
Extension	0.5098**	0.1215	0.2092	0.015
Perceived cost of IPM	-0.0084	-0.0020	0.1432	0.953
Household size	0.0601*	0.0143	0.0328	0.067
Farm size	0.0578	0.0138	0.0735	0.432
Farming experience	-0.0161	-0.0038	0.0256	0.528
Log likelihood	-50.6778			

Note: *significant at 10% alpha level, **significant at 5% alpha level and ***significant at 1% alpha level; mfx = marginal effects; SE = standard error

Effects of IPM on Food Security

The study considered food security from three (3) perspectives, namely, calorie consumption, protein consumption and food expenditure.

Calorie Consumption

Table 6 revealed the determinants of calorie consumption per day of the household in the Study area in 2015. The results in that table revealed that household size was negative and significantly influenced calorie consumption of the households in the area. This implies that as household size increases, calorie intake reduces. An increase in the household size by 1 would decrease the calorie intake by 371 percent. It can be concluded that household with few members consume more calorie than their counterparts with larger household size. The reason for the above might be that as household size increases, less of the household income is spent on calorie consumption of the households and less calorie is available per household member. The result is in agreement with the expectation of the study.

The price of maize determines what an average household will earn from sales of maize and household income level. The price of maize was positive and significantly influenced household calorie consumption. Price of maize was positive and significant at 1 percent alpha level. An increase in the price of maize by ₦1 would increase calorie consumption by 2.4 percent. This implies that the higher the price of maize, the more food secure the households are in the area. The magnitude and sign of maize price was in agreement with the expectation of the study that price of major crop grown increases the income earnings of the households and hence improve their households' consumption.

Length of use of IPM and area under IPM were positive and significantly influenced calorie consumption of the households in the area. They were both significant at 1 percent alpha level each. It is expected that technological change through the adoption of IPM will translate to increased calorie consumption. As length of years of use of IPM increases, calorie consumption of the farming households increases. An increase in the length of year of use by 1 year would increase calorie intake by 3.6 percent. This implies that as the length of year of use of the technology increases, income flow over years would have accumulated, hence households had better buying power to improve on the calorie consumption. Similarly, an increase in the area under IPM would also increase the calorie consumption of the households. An increase in the area under IPM by 1 hectare would increase calorie intake by 880 percent. This implies that as the area under IPM increases, income earnings improve, hence households had better buying power to improve on the calorie consumption.

Protein Consumption

Table 6 revealed the determinants of protein consumption per day of the household in the study area in 2015. The results in the table revealed that off-farm income was positive and significantly influenced protein consumption in the area. Off-farm income was significant at 1 percent alpha level. An increase in the off-farm income by ₦1 would increase protein consumption by 2.3 percent. This implies that off-farm income increases protein consumption among the households. This is in agreement with the expectation of the study that off-farm income increases the purchasing potential of farming households, hence more protein food will be bought and consumed.

Assets and household size were negative and significantly influenced protein consumption in the area. They were both significant at 1 percent alpha level. An increase in the amount spent on assets by ₦1 would decrease protein consumption by 217 percent. Similarly, an increase in the number of households by a unit would decrease protein consumption 955 percent. This implies that as expenses on assets increases, less will be available for household consumption of protein in the area. This is in agreement with the expectation of the study that as more and more assets are bought or acquired by the households, less and less of the protein will be available for the households to consume. In the same vein, as sizes of households in the area increases, protein consumption reduces in the area. The households in the area with small size consume more protein than their counter parts with larger size.

More so, length of use of IPM was positive and significantly influenced protein consumption. It was significant at 1 percent level of probability. It is expected that technological change through the adoption of IPM will translate to increased protein consumption. As length of years of use of IPM increases, protein consumption of the farming households increases. An increase in the length of year by a unit would increase protein intake by 2.6 percent. This implies that as the length of year increases, income flow earned over the years would have accumulated, hence households had better buying power to improve on the protein consumption. This is in agreement with the expectation of the study.

Food Expenditure

Table 6 revealed the parameter estimates for the regression model for the determinants of food security measured by food expenditure. The results in the table revealed that off-farm income was positive and significantly influenced food expenditure among the households in the area. It was positive at 1 percent alpha level. An increase in the off-farm income by a unit would increase food expenditure 2.2 percent. This implies that as an average household earn more off-farm income, more is expended on food. This is in agreement with expectation of the study that as more and more is earned from sources other than farm, more and more will be expended on food.

The price of maize determines what an average household will earn from sales of maize and household income level. The price of maize was positive and significantly influenced household food consumption expenditure. Price of maize was positive and significant at 1 percent alpha level. An increase in the price of maize by ₦1 would increase food consumption expenditure by 4.4 percent. This implies that the higher the price of maize, the more food secure the households in the area. The magnitude and sign of maize price was in agreement with expectation of the study and also in agreement with Akinola (2008) that price of major crop grown by household increases the income earnings of the households, hence improve their consumption. Length of use of IPM and area under IPM were positive and significantly influenced food consumption expenditure of the households in the area. They were both significant at 10 percent alpha level. It is expected that technological change through the adoption of IPM will be translated to increased food consumption expenditure. As length of years of use of IPM increases, food consumption expenditure of the farming households increases. An increase in the length of use by 1year would increase food consumption expenditure by 1 percent. This implies that as the length of year increases, income flow earned over the years would have accumulated, hence households spend more on food consumption expenditure. Similarly, an increase in the area under IPM would also increase the food consumption expenditure of the households. An increase in the area under IPM by 1 hectare would increase food consumption expenditure by 1 percent. This implies that as the area under IPM increases, income earnings improve, hence households would spend more on food consumption. This is agreement with the expectation of the study.

Table 6: Econometric results from instrumental variables of the determinants of food security

Variable	Calorie	Protein	Food expenditure
Constant	50.836***	360.854	66.176
	(12.205)	(0.911)	(14.329)
OFFINCOME	0.025	0.0230***	0.0220***
	(0.052)	(3.801)	(2.734)
ASSETS	0.0000	-2.172***	0.089
	(0.063)	(-8.599)	(0.437)
HHSIZE	-3.710***	-9.553***	0.039
	(-3.738)	(-2.734)	(0.841)
LNEXPSQ	3.267	-10.336	-
	(0.108)	(-1.120)	
LNEXP	-10.215	0.502	-
	(-0.084)	(1.003)	
AGERES	0.084	-276.702	-0.002
	(0.056)	(-3.007)	(-0.216)
EDUCATION	0.061	0.179**	-0.009
	(0.022)	(1.919)	(0.216)
SECONDM	4.768	0.176	0.238
	(0.050)	(0.1447)	(1.466)
SECONDF	-1.271	-41.181	-0.131
	(-0.059)	(-1.001)	(-0.966)
MZPRICE	0.024***	0.457	0.0442***
	(3.000)	(1.537)	(3.469)
IPMUSEDYR	0.036**	0.260***	0.0075*
	(4.001)	(3.083)	(1.902)
IPMAREA	8.800***	0.013	0.740*
	(2.720)	(0.433)	(1.775)
R^2	0.50	0.39	0.24
Adjusted R^2	0.48	0.37	0.22
F-value	27.53	14.81	5.4

*, ** and *** indicate statistical significance at the 10%, 5% and 1% alpha levels, respectively. Figures in parentheses represent t-ratios

Conclusion

The study was conducted to investigate the effects of IPM technology on food security of maize farming households in the study area. Cross-sectional data were collected from 400 maize farming households in the area. The study showed that IPM had positive impact on households' food security in the area. Households that adopted the technology in maize production were more food secure than their counterparts who are not adopters. The findings from the result are in agreement with the purpose of the project as well as provided empirical ground that farming households welfare could be raised through agricultural technological change.

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