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Factors Influencing the Adoption Intensity of Climate-Smart Maize Varieties Among Rural Farming Households in Southern Guinea Savannah of Nigeria.

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Abstract

Farming techniques in sub-Saharan Africa are not improving at the same stride with the advancement of modern agriculture practice. The resultant effects are obscene and foulest recital in agricultural productivity which culminate in food insecurity, impoverishment and a deprived national economy. This paper examines the determinants of intensity of adoption of Climate-Smart Maize Varieties (CSMVs) in the Federal capital territory of Nigeria, using secondary data (IITA SRMV's data). The study used descriptive statistics to analyse the socio-economic characteristics of respondents and a double hurdle model was used to analyse the intensity of adoption of CSMVs. The results indicate that the level of awareness was 47 percent, while the adoption rate was 53 percent. The results further indicate that age, contact with the extension agent, and marital status significantly influenced the intensity of (CSMV) adoption.

The study recommended that adequate policies and development programs for promoting the use of climate-smart maize varieties in Nigeria should be directed towards input and output delivery, land under climate-smart maize varieties, extension service provision, affordable credit, education, and mechanism that are more effective as well as youth-oriented initiatives. Furthermore, farmers should be encouraged to join groups (farmer groups, cooperatives) in order to build their social capital, which could expose them to better practices, obtain informal training from those who have adopted them, and obtain help for implementation.

Keyword*s:* Adoption, Climate-smart maize varieties, intensity, extension access, Double hurdle

1.0 Introduction

Although the Nigerian Economy is largely agrarian, the country still depends on its oil sector, and it accounts for 75% of its annual revenue. The agricultural sector employs more than 50% of the country's agricultural labour force actively engaged in subsistence production (22). Agriculture plays a leading role in providing raw materials for industries and contributes about 21.20% to the country's GDP through its foreign earnings (30). The agricultural sector is multi-sectoral, promotes positive change in rural and urban areas, and as such, is essential for influencing economic growth and development, and enhancing food security (13).

In Nigeria (and sub-Saharan Africa) at large, maize is an important staple food and the most important cereal crop after maize and millet (25). Its importance in economic growth cannot be underemphasized as it contributes to food security and poverty alleviation. The Southwestern Zone of Nigeria previously dominated maize production but recently, it has been documented from literature that production of dry maize has shifted to the Southern Guinea Savannah (17). Due to high solar radiation and low night temperature, the region has a comparative advantage in the production of maize over the other zones (20;10). Low maize productivity in Nigeria is attributed to the poor seed supply system, unavailability and/or ineffective use of herbicides, fertilizers, and improved seeds, increasing levels of biotic and abiotic constraints, dearth of investments in research and development, inefficient market systems, fluctuating input prices, and at large; global warming (18).

In southern guinea savannah of Nigeria, research organizations such as the International Institute of Tropical Agriculture (IITA) and National Agricultural Seeds Council have prioritized the development (and timely dissemination) of climate-smart, as well as disease and drought-resistant seeds to maize farmers at affordable prices (6). These seeds offer unique characteristics such as shorter maturity periods, higher yield as well as tolerance and resistance to pests and diseases. Adoption of climate-smart maize varieties is vital to ensuring that the increasing food demand of the ever-increasing population is constantly met. Adoption of climate-smart and improved farming technology remains the obvious pathway for breaking the poverty cycle, which affects the quality of life of rural farmers (7). When adequately applied, climate-smart maize varieties would increase productivity, provide additional income, and improve farmers' welfare. Despite these, the adoption of climate-smart maize varieties has not translated to improved welfare among maize farming households (19).

Maize is of strategic importance to food security, but its productivity is threatened by the cultivation of local and unimproved varieties in the Southern Guinea Savannah of Nigeria, which limits farm output and productivity. Since the 1980s, CGAIR scientists at International Maize and Wheat Improvement Centre have intensified efforts toward developing drought-resistant maize varieties to improve climate resilience, ensure food security, and improve farmers' livelihood. Despite the availability of climate-smart maize varieties, maize farmers have been unable to take advantage of these technologies due to low savings, low capital, low output, and low income; hence, they are trapped in the vicious cycle of poverty (24). Therefore, this study investigates the factors influencing the adoption intensity of climate-smart maize varieties among rural farming households in Southern Guinea Savannah of Nigeria.

Previous studies have majored on the rate of adoption of improved maize varieties and predisposing factors (1) and effect of improved maize variety adoption on productivity (28). Although, in accessing adoption intensity, different analytical tools such as Average Treatment Effect (7); instrumental variable (11) and double difference (27). Some previous studies also used non-random sampling to select maize farmers into the treatment group and as such, heterogeneity bias becomes imminent. However, this study employed random selection of maize farming households so that the Double Hurdle model can be used to obtain statistically significant results.

2.0 Literature Review

The different theories developed through reviews of previous studies with tested knowledge of the study variables as well as the specific theory to be adopted for this study are presented in this section. The various theories include Diffusion of innovation theory by which explains that in any social system, adoption is not occurring simultaneously but at a different pace, as some farmers adopt early, some adopt late while others may never adopt; Theory of Task-Technology fit which according to (14), a good fit between task and technology increases the likelihood of utilization, and performance since the technology meets the needs of users; and the theory of planned behavior by (3).

The different methodologies for measuring adoption intensity includes Double hurdle regression (19, 8, & 22), Logit regression (30 & 21), and Tobit regression (5 &16). Amount of credit ($p<0.1$), age($p<0.05$), age squared ($p<0.05$), use of hired labour ($p<0.1$), and gender ($p<0.05$) were determinants of adoption of improved cassava varieties in South-western Nigeria (14); Access to credit ($p<0.01$), access to participation in social organization ($p<0.05$), labour ($p<0.01$), farming experience ($p<0.05$), household size ($p<0.05$), farm size ($p<0.1$), distance to main road ($p<0.01$), total livestock unit ($p<0.01$), access to input supply ($p<0.05$), and farm income ($p<0.01$) influenced the adoption of improved bread wheat varieties (30); and Level of education (p<0.01), household size (p<0.05) and farm size (p<0.01) were the Socio-economic factors affecting the extent of adoption of improved soybean seeds in Borno State, Nigeria (15).

3.0. Materials and Methods

The study area was Abuja, the Federal Capital Territory (FCT). Abuja comprises of six (6) area councils, namely; Abaji, Abuja, Bwari, Gwagwalada, Kuje and Kwali. FCT shares land borders with Niger, Kogi, Nassarawa to the West and East and South of Nigeria, respectively. The land area is 242 425km^2. As of 2017 the population was a 2.4million (National Population Commission, 2018). Abuja belongs to the Guinea Savannah agro-ecological zone with an average annual rainfall of 1200 - 1500mm and annual temperature ranging from 22.55 ± 0.42^{o}C - 33.54 ± 0.23^{o}C. Annual relative humidity ranges between 50.08 - 52.75%.

Secondary data obtained from the survey conducted by International Institute of Tropical Agriculture (IITA) in 2016 was used for the study. This survey was conducted as part of the Drought Tolerant Maize for Africa (DTMA) research project by the International Institute of Tropical Agriculture (IITA) and the International Maize and Wheat Improvement Center (CIMMYT). The DTMA project is part of the CGIAR research program on maize and funded by the Bill and Melinda Gate foundation (BMGF). It was collected in 2016 with the use of well-structured questionnaires.

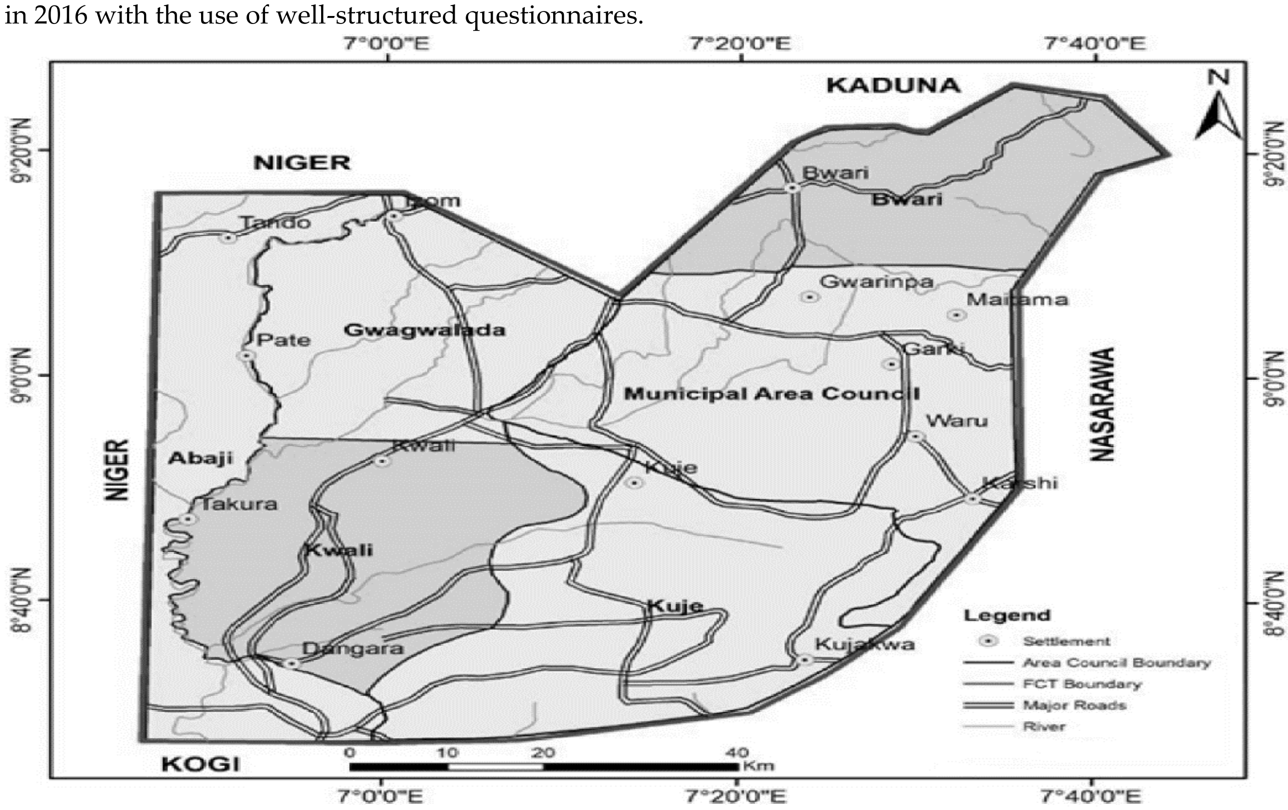

Fig 1: Map of the Study Area.

A three-stage sampling procedure was employed in this study. The first stage was the purposive selection of the Federal Capital Territory, Abuja. The second stage involved the use of random sampling technique to select four out of the six area councils in the Federal Capital Territory (**See Figure 1**). The third stage involved the random selection of four areas out of the four previously selected area councils. The fourth stage was the random selection of maize farming households (proportionate to district size) due to the varying population of the selected area councils. Out of the 950 questionnaires administered, only 843 had complete information and formed the sample size of the study.

Descriptive statistics such as a table, frequency, charts, and Double-Hurdle model were employed for the data analysis.

Double hurdle regression

The double-hurdle model is a parametric generalization of the Tobit model, in which two different stochastic processes determine the adoption decision and adoption intensity of climate-smart maize varieties.

The double-hurdle model has an adoption (D) equation:

$$D_i = 1 \; if \; D_i * > 0 \; and \; 0 \; if \; D_i * < 0 \ldots\ldots\ldots\ldots\ldots..(1)$$

$$D_i = \alpha' Z_i + u_i \ldots\ldots\ldots\ldots..(2)$$

being D^* a latent variable that takes the value 1 if the farmer adopts improved varieties and zero otherwise, Z is a vector of household characteristics and α is a vector of parameters.

The level of adoption (γ) has an equation of the following:

$$\begin{bmatrix} Y_i = Y_i^* if \; Y_i^* > 0 \; and \; D_i^* > 0 \\ Y_i = 0 \\ \quad Y_i^* = \beta' X_j + V_i \end{bmatrix} \ldots\ldots\ldots\ldots\ldots\ldots.(3)$$

Where y_i is the observed answer to the proportion of improved varieties, X is a vector of the individual's characteristics and β is a vector of parameters. The log-likelihood function for the double-hurdle model is:

$$\log l = \sum_{0}^{1} ln\left[1 - \Phi\left(\alpha Z_i^{'}\right)\left(\frac{\beta X_i'}{\sigma}\right)\right] + \sum_{0}^{1} ln\left[\Phi(\alpha Z_i')\frac{1}{\sigma}\,\phi\left(\frac{Y_i - \beta X_i'}{\sigma}\right)\right] \ldots\ldots\ldots.(4)$$

A simple test for the double-hurdle mode against the Tobit model can be used. It can be shown that the Tobit log-likelihood is the sum of the log-likelihood of the truncated and the Probit models. Therefore, one simply must estimate the truncated regression model, the Tobit model, and the Probit model separately and use a likelihood ratio (LR) test. Previous related studies that used double-hurdle regression include Awotide *et al*. (2014) and Okoffo *et al*. (2016).

3.0 Results and Discussion

3.1 Socioeconomic characteristics of the Maize Farmers

The socioeconomic characteristics of the maize farmers are presented in table 1. The distribution of the age of farmers shows that majority of the adopters were within the age bracket of 39-48 years (29%), while the majority of non-adopters were also within the age bracket of 39-48 years (32.07%). Farmers within the age bracket of 89 – 988 years accounted for the most minor proportion of adopters (0.2%), while farmers within the age bracket of 79 – 88 years had the least proportion among non-adopters (0.29%). The mean age of non-adopters stood at 44.5 ± 13.3 years, while the mean age of the adopters was 43.9±12.85 years. This implies that the majority of the adopters and non-adopters are economically active adults in their productive ages. Farming is the primary occupation in the study area, and it employs the young and active. This finding is similar to that of Oladimeji *et al.* (2017), who found that the mean age among the households is 42 years but with a marginal difference. The distribution of farmers by sex revealed that the majority of the farmers (90.0%), non-adopters and adopters, were male, while (10.0%) were females for both the non-adopters and adopters (See Table 1a). This implies that maize farming is a male-dominated enterprise in the study area. This agrees with the findings of Enete and Amusa, (2010) who revealed that males dominate maize farming activities. This is because men are more concentrated on the farm than their female counterparts who are also involved in off-farm; and because maize farming is tedious work, which requires strength. The distribution of level of education (See Table 1a) shows that 21.0% of the non-adopters had no formal education while 33.2% and 29.2% and 16.6% had primary, secondary and tertiary level of education respectively. In addition, the table further reveals that 23.0% of the adopters had no formal education while 25.8%, 32.2%, 19.0% had primary, secondary and tertiary level of education respectively. This is corroborated by the findings of Shiferaw *et al.* 2014 that majority of the farmers in the study area were literate. The distribution of respondents by the main occupation shows that the majority of the non-adopters (54.21%) and adopters (36.66%) had farming as their primary occupation. In comparison, 1.66% are salaried earners for both adopters and non-adopters, and 2.14% and 0.95% are self-employed off-farm for non-adopters and non-adopters respectively. This implies that the majority (90.87%) of the farmers engaged in farming as their main occupation. This may be because of the availability of land and family labour. The distribution of the marital status of the farmers shows that majority of the non-adopters (94.4%) and the adopters (90.7%) are married, while 5.3% and 3.7% of the adopter and non-adopters respectively are never married. This implies that a greater percentage of the respondents were married while only few were never married. This result corroborates the findings of Awotide (2012) that the majority of adopters were married. The farm size distribution of the farmers reveals that most non-adopters (74.5%) and adopters (73.5%) cultivated less than 5 hectares. This indicated that the majority of the two categories of farmers cultivated less than 5 hectares of farmland. The average cultivated land for the farmers is about 1.3ha. This is consistent with the findings of (Akinola *et al*. 2010) who affirmed that the mean farm size of small-scale farmers in Ogun state was below 3ha. More than 49% of the adopters cultivated 2.0 - 4.99ha while 42.9% of the non-adopters also cultivated similar farm sizes, which are lesser than 5ha.

The distribution of the farmers by the status of adoption shows that majority of the farmers (52.80%) are non-adopters of climate-smart maize varieties (See Figure 2). This is in line with the findings of Umeghalu and Okonkwo (2013) that the adoption of new technologies in rural areas is still relatively low. Farmers are still risk averse majorly because of low resources and are unwilling to invest in a venture they are unfamiliar with. About 61.20% of the non-adopters had no access to market information while 47.20% of the adopters had access to market information (See Figure 3). This indicates that adopters had more access to market information. This is consistent with the findings of Kizza *et al*. (2011) who affirmed that market information influenced the adoption of new technology. The distribution of contact with extension agents of the farmers reveals that 71.8% of the non-adopters and 67.9% of the non-adopters (67.9%) had contact with extension agents, respectively (See Figure 4). This indicates that non-adopters had more contact with extension agents than adopters. Also, about 66.0% of the non-adopters and 63.3% of the adopters used fertilizer on their farms. This implies farmers' accessibility to fertilizer in the study area. This is in line with the findings of Obisesan *et al*. (2013**),** who affirm that access to fertilizer is very high among farmers. The distribution of household income of the farmers in Table 1b reveals that 26.2% of the non-adopters of climate-smart maize varieties made an income of ₦20000-₦150000 per cropping season while 25.4% of the adopters earned ₦500001-₦1000000 per cropping season. This indicated that the majority of the adopters made a relatively higher income compared to the non-adopters. The average income per cropping season was also reported to be ₦682,536 among the maize farmers.

3.2 Probit Regression Estimates of factors influencing the adoption of climate-smart maize varieties.

Table 2 shows the factors influencing the adoption of climate-smart maize varieties. The regression results show that a Chi-squared of 30.30 is significant at 1% (0.0025), indicating that the model is statistically fit and can be used for econometric prediction. Also, a Pseudo R-squared of 0.266 suggests that 26.6% of the independent variables were explained in the model. The result revealed that three independent variables: access to market information ($p<0.01$), marital status ($p<0.05$), and main occupation ($p<0.1$) significantly influenced respondents' adoption of climate-smart maize varieties. Each of the significant independent variables is explained below. Access to market information had a positive and significant relationship ($p<0.01$) with the adoption of climate-smart maize varieties. It reveals that an increase in market information access will lead to a 13.65% increase in the adoption of climate-smart maize varieties. This means that as access to market information by the respondents' increases, adoption of climate-smart maize variety increases. This agrees with the findings of (Awotide *et al.* 2016), increase in awareness and marketing level increases the likelihood of adopting improved rice varieties. Farmers that read about the increased yield of a new variety will most likely adopt the variety. The marital status of the farmer was significant ($p<0.05$) and showed a positive relationship with the respondents' likelihood of adopting climate-smart maize variety. This means that married respondents have a higher likelihood of adopting climate-smart maize variety. The marginal effect also means that, for married respondents the likelihood of adopting climate-smart maize variety increases by 14.15% compared to unmarried respondents. Umar *et al.* (2014) obtained similar results. Main occupation of the respondents was significant ($p<0.1$) and showed a positive relationship with the respondents' likelihood of adopting climate-smart resistant maize variety. This means that respondents who are primarily farmers have a higher likelihood of adopting climate-smart maize varieties. The marginal effect also indicates that farming households' likelihood of adopting climate-smart maize variety increases by 6.21% compared to non-farming households.

3.3. Tobit regression factor influencing the intensity of adoption climate-smart maize varieties

Table 3 shows the factors influencing the intensity of the adoption climate-smart maize varieties by maize farmers. The results show that a Chi-squared of 14.49 is significant at 1% (0.0087), indicating that the model is statistically fit and can be used for econometric prediction. Also, a Pseudo R-squared of 0.2068 suggests that 20.68% of the independent variables were explained in the model. The result shows that four independent variables: age ($p<0.1$), age squared ($p<0.1$), contact with extension agent ($p<0.1$), and marital status ($p<0.05$) significantly influenced respondents' intensity of climate-smart maize variety adoption in the study area. The result shows that age had a positive and significant relationship ($p<0.1$) with the intensity of adoption of climate-smart maize variety. It reveals that a unit increase in age of the respondent will lead to 3.23% increase in the intensity of adoption of CSMVs. This means that as age increases, the intensity of adoption of CSMVs increases. This is in line with the findings of Abebe *et al*. 2013 that an increase in age increases the likelihood of adopting improved maize varieties. Contact with extension agent was significant ($p<0.1$) and shows a positive relationship with the intensity of adoption of climate-smart maize variety among respondents. This means that respondents that had previous contacts with extension agents are likely to have higher intensity of adoption of climate-smart maize variety. The marginal effect also means that, contact with extension agents increases the intensity of adoption of CSMVs variety by 9.40% compared to non-farming households. This may be attributed to the awareness of CSMVs caused by contact with extension agents. This finding is similar to that of Abdoulaye *et al.* (2014), that awareness increases the likelihood of adoption among farmers. Marital status was significant ($p<0.05$) and shows a negative relationship with the respondents' intensity of adoption of CSMVs. This means that the intensity of adoption of CSMVs is higher among unmarried respondents. The marginal effect also means that, for unmarried respondents, the intensity of adoption of CSMVs increases by 31.42% compared to married respondents.

5.0 Conclusion and Recommendations

Adoption has become an increasingly important concept in agricultural policy as it both affords the option of increasing welfare and reducing poverty. The Adoption of climate-smart maize varieties has a positive impact on the welfare of farming households in the study area. It increases the streams of income to maize-farming households and as a result, improves the welfare status of farming households in the study area. In addition, access to market information, marital status, and the main occupation of the respondents increased the likelihood of maize farmers' adoption of climate-smart maize varieties in the study area and income per cropping season of adopter's climate-smart maize varieties was relatively higher than that of non-adopters.

Based on the findings of the study, the study recommended that adequate policies and development programs for promoting the use of climate-smart maize varieties in Nigeria should be directed towards input and output delivery, land under climate-smart maize varieties, extension service provision, affordable credit, education, and the mechanism that are more effective as well as youth-oriented initiatives. Furthermore, farmers should be encouraged to join groups (farmer groups, cooperatives) to build their social capital, which could expose them to better practices, obtain informal training from those who have adopted them, and obtain help for implementation.

List of Tables

Table 1a: Distribution of respondents' socio-economic characteristics.

Socio-economic characteristics	Non-adopters		Adopters		Total	
	Freq.	Percentage	Freq.	Percentage	Freq.	Percentage
Age (Years)						
19 - 39	179	35.8	118	34.40	297	35.23
40 - 59	243	48.6	180	52.48	423	50.17
60 - 79	71	14.2	44	12.83	115	13.64
80 and Above	7	1.4	1	0.3	8	0.9
Total	500	100	343	100	843	100
Mean	44.5					
Std. Deviation	13.3					
Skewness	0.696					
Level of Education						
No education	105	21	80	23.0	185	21.9
Primary	166	33.2	89	25.8	255	26.7
secondary	146	29.2	109	32.2	255	26.7
Tertiary	83	16.6	65	19	148	17.6
Total	500	100	343	100	843	100
Main Occupation						
None	7	0.83	4	0.76	11	1.30
Farming (crop & livestock)	457	54.21	309	36.66	766	91.46
Salaried employment						
Self-employed off-farm	15	1.78	14	1.66	29	3.44
Casual labourer on-farm	18	2.14	8	0.95	26	3.08
Casual labourer off-farm						
Total	1	0.19	2	0.38	3	0.36
	2	0.38	1	0.19	3	0.36
	500	59	343	41	843	100
Marital status						
Married	472	94.4	311	90.7	783	92.9
Divorced	2	0.4	0	0	2	0.5
Widow/widower	8	1.6	14	4.1	22	2.6
Never married	18	3.6	18	5.3	36	4.3
Total	500	100	343	100	843	100

Farm size						
< 5	373	74.6	252	73.5	625	74.1
5.1-10	95	19.0	72	20.9	167	19.8
> 10	32	6.4	19	5.5	51	6.1
Total	500	100	343	100	843	100
Household income per cropping season (₦)						
< 20,000						
20,001 – 150,000	35	7.0	19	5.5	54	6.4
150,001 – 300,000	131	26.2	58	16.9	189	22.4
300,001 – 500,000	93	18.6	59	17.2	152	18.0
500,001 – 1,000,000	71	14.2	45	13.1	116	13.8
1,000,000- 3,000,000	106	21.2	87	25.4	193	22.9
> 3,000,000	51	10.2	66	19.2	117	13.9
	13	2.6	9	2.6	22	2.61

Source: Author's Computation, 2021

Table 2: Probit Regression Estimates of factors influencing the adoption of climate-smart maize varieties

Variable	Coef	St. Er.	P>|Z|
Sex	-0.009	0.1553	0.954
Age	-0.002	0.0038	0.613
Years of Education	0.0015	0.0091	0.869
Access to market information	0.3534***	0.0924	0.000
Contact with extension agent	0.0492	0.1019	0.692
Income per cropping season	4.38E-08	3.20E-08	0.171
Access to training	-0.0128	0.1090	0.906
Farm size	-0.0119	0.0078	0.125
Marital status	0.3537**	0.1628	0.030
Household head type	0.0356	0.0371	0.337
Access to credit	-0.0288	0.1893	0.897
Main occupation	0.1627***	0.0865	0.060
Constant	-0.2063	0.3931	0.060
No. of Obs. =843, LR Chi2 (12) =30.30, Pseudo-R2 =0.266, Prob > chi2 =0.0025, Log likelihood= -554.47			

Source: Author's Computation, 2021

Table 3: Tobit regression factor influencing the intensity of adoption climate-smart maize varieties

Variable	Coef.	Std. Err.	P>|Z|
Sex	-0.0252	0.1457	0.863
Age	0.0323*	0.0190	0.089
Age squared	-0.0003*	0.0001	0.075
Years of Education	0.0019	0.0085	0.823
Contact with extension agent	0.1616*	0.0940	0.086
Training on striga management	0.0004	0.0008	0.651
Use of fertilizer	-0.1126	0.0887	0.205
Farm size (ha)	-0.0107	0.0074	0.144
Marital status	-0.3147**	0.1480	0.034
Household head type	0.0211	0.0343	0.539
Access to credit	-0.0203	0.1711	0.909
Constant	-0.5853	0.5348	0.274

Number of Obs.= 843, LR chi2(11)= 14.49, Prob > chi2= 0.0087, Pseudo R2 = 0.2068, Log likelihood = -822.8213

Source: Author's computation, 2021

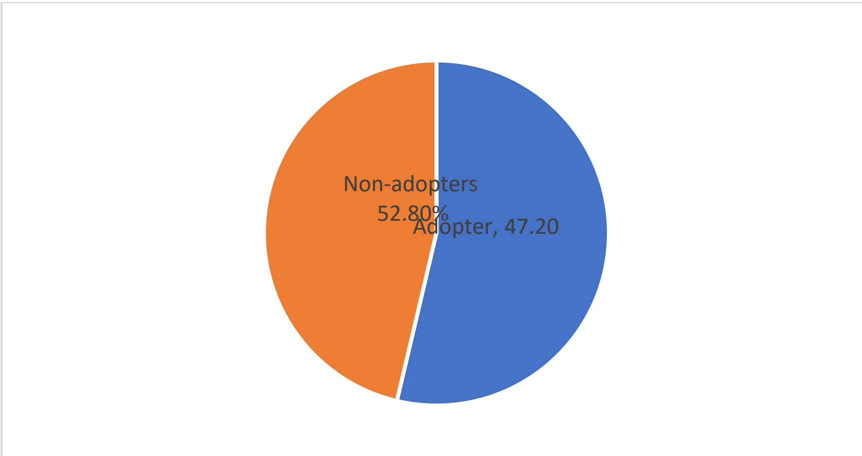

Figure 2: Distribution of farmers by status of adoption.
Source: Author's Computation 2021
Source: Author's Computation (2015)

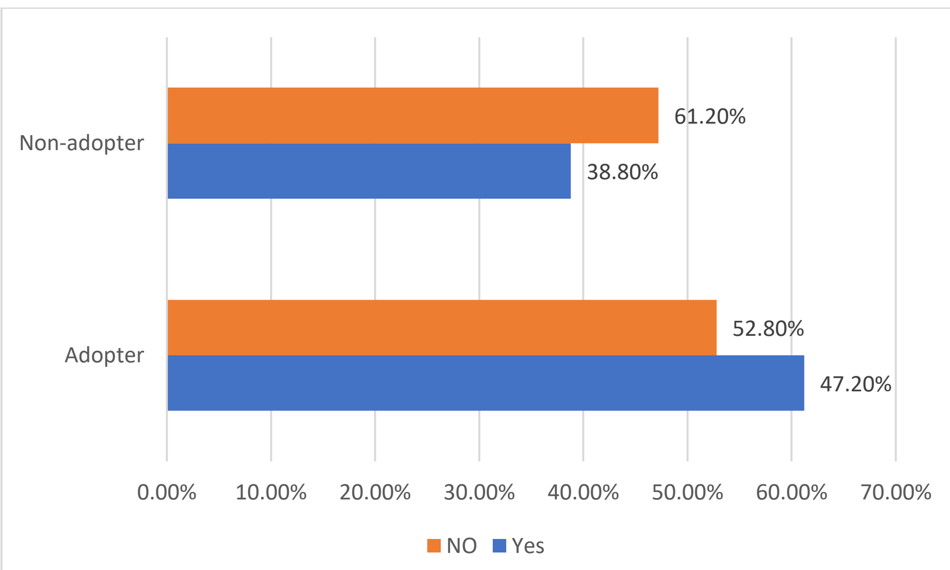

Figure 3: Distribution of respondents by access to market information
Source: Author's Computation 2021.

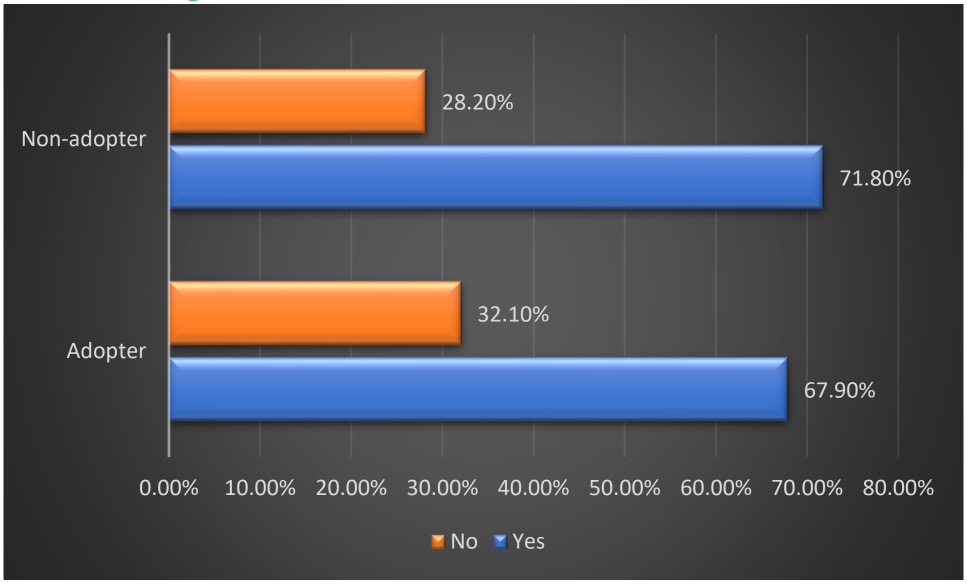

Figure 4: Distribution of respondents by contact with extension agents.
Source: Author's Computation 2021.

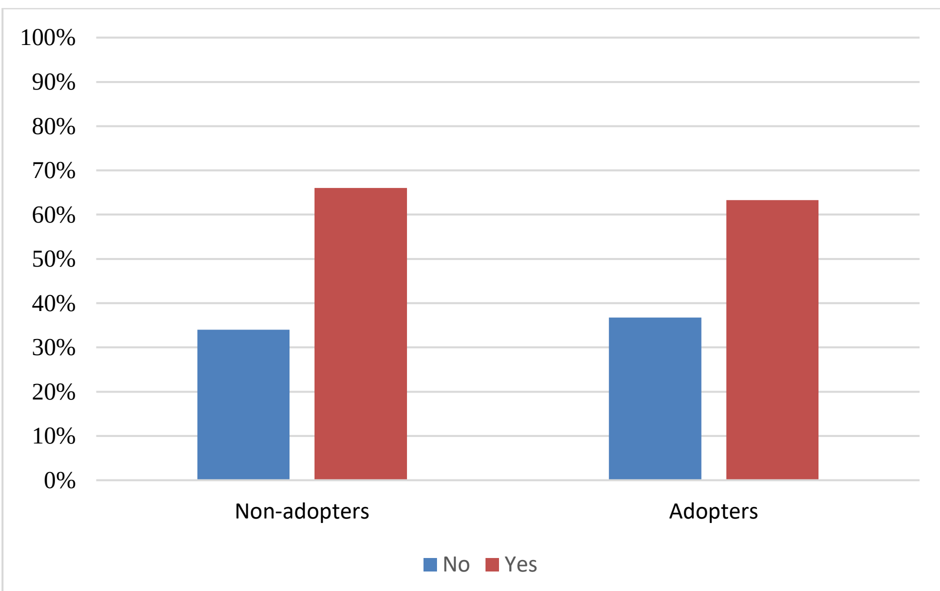

Figure 5: Distribution of fertilizer use by the respondents.
Source: Author's Computation 2021.

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