ISSN 2521 – 0408
AEXTJ
AGRICULTURAL EXTENSION JOURNAL

Available Online at www.aextj.com
Agricultural Extension Journal 2018; 2(3):165-175

RESEARCH ARTICLE

Determinants of Adoption of Improved Maize Technology among Smallholder Maize Farmers in the Bawku West District of the Upper East Region of Ghana

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Received: 20-10-2018; Revised: 26-11-2018; Accepted: 04-12-2018

ABSTRACT

Introduction: As part of Ghana's agricultural modernization agenda aimed at ensuring the National Food Security, the Ministry of Food and Agriculture (MOFA) through its extension directorate has been promoting the adoption of improved maize technologies. **Method and Material:** This paper presents the finding of a study conducted to assess the determinants of adoption of improved maize technologies among smallholder farmers in the Bawku West District of the Upper East Region of Ghana. Exploratory survey design was employed with multistage sampling techniques adopted in selecting 400 maize farmers for the study. **Result:** Personal interviews, administration of semi-structured questionnaire, observations, and focus group discussions were the main methods employed in data collection. Probit regression model was applied in analyzing determinants of the adoption of improved maize technologies. Household annual income, access to labor, access to credit, and extension contact were found as significant determinants of farmers' level of adoption of improved maize technology. **Conclusion:** The study recommends to the MOFA to promote the use of labor saving simple farm tools in carrying out the various production recommendations under the improved maize technology. Furthermore, MOFA needs to work with financial institutions to support maize farmers with credit to enable them to acquire the necessary inputs required in the implementation of the improved maize technology.

Key words: Adoption, determinants, improved maize technology, production recommendations, smallholder farmers

INTRODUCTION

History is awash with evidence to the fact that agriculture and economic development are intricately linked. It has been argued that no country has ever sustained rapid economic productivity without first solving the problem of food insecurity and the nutritional challenge of her populates.[1,2] According to Juma,[1] evidence from industrialized countries, as well as countries that are rapidly developing today, amply demonstrates that agriculture stimulated growth in other sectors and supported overall economic development and general well-being of people.

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It is a common knowledge that agricultural development and farm productivity have largely been driven by advances in science and technology which have helped to generate a better understanding of crops and animals leading to breeding of high yielding, disease, and pest resistance varieties of crops and better-performing livestock.[3] The green revolution in Europe and some part of Asia had demonstrated aptly the significant impact of agricultural technology adoption on farm productivity and national development.[3-6]

However, Abate *et al.*[3] observed that this development is yet to manifest in many African countries, especially in countries south of the Sahara. Although modern technologies, such as improved seeds, fertilizer, and agrochemicals, are readily available, their rates of adoption have been the lowest in Africa.[7,8] As a result, the continent has the largest yield gaps (i.e., the difference between possible and actual yields) in major cereals such as rice and maize.

Ghana has expressed policy for leveraging on agricultural growth for overall national development (FASDEP I and II, GPRS I and II and GSGDA). As a result, the agricultural sector in Ghana is widely regarded as an important engine of growth and pathway out of poverty, especially among the rural poor. In the National Development Agenda, agriculture is expected to lead the growth and structural transformation of the economy.[9,10] As a result, successful governments have implemented a series of projects aimed at agricultural modernization and sustainable agricultural production. Promotion of technology-based agricultural production propelled by research and development (R and D) and vigorous extension activities have long been implemented to facilitate the adoption of improved farming technologies and practices.

However, the agricultural sector in Ghana had witnessed a consistent decline in its contribution to national GDP within the past decade. The sector contribution to national GDP dropped from 31% in 2008 to just 20.1% in 2016, with growth rate falling from 7.4 to 3.6 within the same period[11,12] registering average annual growth rate of 4.1 compared with 6% annual growth rate envisaged in the country's Medium Term Agricultural Sector Investment Plan. This has been largely attributed to low technology adoption, high cost of agricultural inputs, particularly agrochemical and machineries.[9] This led to the re-introduction of agricultural subsidy program in 2008 with a particular focus on agrochemical to increase use of fertilizer in line with the Abuja declaration. As part of the national food security strategy, the effort is being made to improve the production and productivity of major staples such as maize, rice, and cassava which are widely cultivated and consumed in the country.[9,10]

Maize is the most important staple crop in Ghana and accounts for >50% of total cereal production in the country.[10,13] It is the second most important crop in the country after cocoa.[10,13] The bulk of maize produced goes into food consumption, and it is certainly the most important crop for food security.[13] The maize sub-sector in Ghana has witnessed the implementation of many projects and research activities aimed at improving maize production and productivity. Notable among them are the Ghana Grains Development Project and the Sasakawa Global 2000 Maize Improvement Programme. Despite these efforts, maize yield and productivity had not improved much.[13,14]

As observed by International Food Policy Research Institute[14] and also cited in the Ministry of Food and Agriculture (MOFA),[9] yields are generally less than half of economically attainable yields for staple crops such as maize and rice. For example, national average yields range between 1.7 metric tons/hectare and 2.5 tons/hectare for maize and rice, respectively.[9,10] However, data from different on-station and on-farm trials suggest that yield averages of 4–6 tons/hectare for maize and 6–8 tons/hectare for paddy rice are achievable.[14] This huge yield gap can be bridged through the adoption of improved technologies.

In response, the MOFA through its extension directorate has been promoting the adoption of improved maize technologies particularly, use of improved seeds, best agronomic practices, used of fertilizer, post-harvest management for over two decades. Notwithstanding, many studies still attribute the wide yield gap in maize to low adoption of productivity-enhancing technologies, including improved varieties and management practices, and low use of purchased inputs, especially fertilizer.[9,10,14] This paper, therefore, presents the finding of a study which assessed determinants of adoption of improved maize technology among smallholder farmers in the Bawku West District of the Upper East Region of Ghana.

Theoretical framework

Theoretically, many models and theories have postulated some understanding of technology adoption or acceptance behavior. One of the well-known models related to technology acceptance is the Technology Acceptance Model (TAM), originally proposed by Davis.[15,16] TAM has proven to be a theoretical model in helping to explain and predict user behavior toward information technology. Rogers[17] classified factors influencing technology diffusion as innovation factors, factors relating to characteristics of end users and institutional framework promoting and disseminating the innovation. The innovation factors are attributes of the innovation such as relative advantage of the innovation relative to existing technologies, compatibility of the innovation and innovation complexity.

TAM has proven to be a theoretical model in helping to explain and predict innovation adoption behavior of prospective users.[18] TAM is considered an influential extension of theory of reasoned action (TRA) proposed by Fishbein and Ajzen[19] which postulates that individual technology adoption intention is significantly determined by their perception and attitude toward the technology and subjective to social norm. Venkatesh and Davis[20] commenting on the applicability of TRA in explaining the influence of social pressure on behavior indicated that the TRA holds that the practical impact of subjective norm on behavioral intention is that an individual may choose to perform a specific behavior, even though it may not be favorable to him or her to do so but just to conform with social norms. Furtherance of TRA is the theory of planned behavior (TPB) which postulates that antecedent to behavior is intention which determines by individual perception and attitude toward the said behavior. TPB also acknowledged societal influence, referred to as social norms, and perceived behavioral control, which captured individual perception about the consequences of behavior, in determining individual behavioral intention.[21,22]

Conceptual framework and literature

Guided by TAM and TRA, this study conceptualized farmers' technology adoption behavior as their disposition toward accepting and using technology disseminated to improve maize production in the district. The factors which influence technology adoption are conceptualized in this study as external factors (factors outside the technology attributes) such as farmers' characteristics, access to information, and credit among others, and innovation attributes such as perceived usefulness of the innovation and perceived ease of use of the innovation, all of which influence farmers' attitudes toward the innovation and therefore their behavioral intention concerning the innovation.

Figure 1 presents the schematic demonstration of these narratives. As shown in Figure 1, the study conceptualized that external factors such as socioeconomic and farm characteristics will shape how farmers see the usefulness of the improved maize technology as well perceived ease of use of the technology. Literate farmers are expected to better understand the production recommendations and as such will be in the better position to appreciate their usefulness and their application. Similarly, more experienced farmers who have been practicing agronomic practices of maize production will be more likely to appreciate the technologies than less experience ones.

Furthermore, the way that farmers see how useful the technologies are (perceived usefulness) and

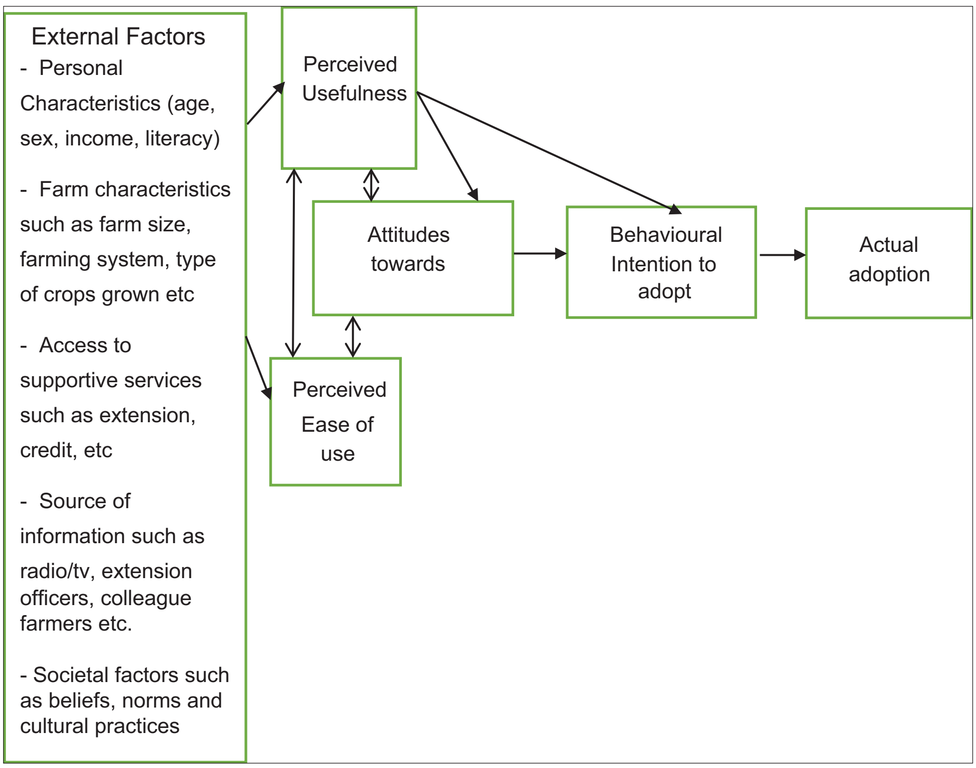

Figure 1: Conceptual framework. Source: Adapted from Davis[15]

how ease or difficult it is to apply them (perceived ease) is conceptualized to have direct influence on their attitude toward the technology and hence their adoption intention and actual adoption.

METHODOLOGY

The study was conducted in the Bawku West District of the Upper Region of Ghana. The district was selected because it is among the major maize growing districts in the region. The Bawku West District can be located within the northeastern area of the Upper East Region and lies roughly between latitude 10^0 30'N and 11^0 10'N and between longitudes 0^0 20'E and 0^0 35'E (GIS, 2014).[23] The district shares boundary to the north by the Province of Zabre in neighboring Burkina Faso, to the east by the Binduri and Garu-Tempane Districts, to the west by the Talensi and Nabdam Districts, respectively, and to the south by the Mamprusi East District [Figure 2].

Agriculture constitutes the dominant economic activity in the district with >80% of the active population deriving their income and livelihood from agriculture. The total arable land in the districts is 58,406 ha.[24] The main agriculture activities in the dsistrict include crops farming, livestock, and agriculture-related activities mainly agro-processing such as pito brewing, shea butter extraction, groundnut oil extraction, malt production, rice processing, and dawadawa processing.[24]

Figure 2: Map of Bawku West District. Source: GIS[23]

Population and sample size determination

All maize farmers in the district constituted the population of this study. List of maize farmers in all the 24 operational areas in the district was sourced from the district department of agriculture. From the list, about 5750 farmers were introduced to the improved maize technology. Therefore, the target population for the study was 5750 farmers. Cochran's sample size determination formula was employed in determining the sample size. Applying Cochran,[25] sample size (n) computation formula as:

$$n = \frac{N}{1 + Ne^2}$$

Where n = sample size
N = population of maize farmers who have been introduced with the technology
e = marginal error (5%)
Information gathered from MOFA in the district gave the total number of maize farmers who have been introduced to the improved maize technology as 5750 farmers. Thus, N = 5750.

$$n = \frac{5750}{1 + 5750(0.05)^2} = 373.4$$

Thus, n = 374 maize farmers. Adding 10% for unforeseen circumstances brings the total sample size targeted as 411 maize farmers. However, 11 farmers sampled could not be reached for an interview. Therefore, the sample size used in the study was 400 maize farmers.

Multistage sampling technique was employed in selecting respondents from the target population. The Bawku West District was purposively selected because it is one of the leading maize producing districts in the upper east region. Furthermore, many NGOs such as Techno-serve, ADVANCE USAID, and ADDRO are actively working in the district to promote technology adoption in maize production. This was followed by stratified random sampling techniques in which the district was stratified along the 24 MOFA operational areas. The 24 operational areas were found not to differ much by the number of maize farmers per the records of AEAs operating in the areas. As such equal proportion was selected from each operational area. With the total sample size of 400 farmers, 17 farmers were selected from 16 operational areas and 16 farmers from the remaining 8 operational areas. From the list of maize farmers introduced to the improved maize technology, lottery method of simple random sampling technique was applied in sampling respondents from each operational area.

Data collection methods

Both primary and secondary data were sourced from the sampled farmers, the district department of agriculture and the NGOs working in the district to help improve agricultural production and rural development. Personal interviews, focus group discussions, key informant interviews, and in-depth interviews were employed in collecting primary data. While documentary reviews, web search and reports were employed in gathering secondary data for the study.

Semi-structured questionnaire was developed and validated by senior academics and research officers in the faculty and the district MOFA office. Questionnaires were then pre-tested in two communities in the Nabdam district. The questionnaires were administered to the sampled farmers in their dialect (Kusaal). Since the lead researcher, as well as the research assistants, could speak the language, language barriers were not a problem. Farmers were interviewed in their homes and farms, which allowed enumerators to also observe farmers' practices relevant to the study.

With the aid of a checklist, nine focus group discussions were held in which farmers discussed issues ranging from maize production, technology adoption, access to agricultural information, challenges, and constraints limiting their technology adoption. The lead researcher facilitated al the nine focus group discussions with the help of two assistant researchers/enumerators.

Data analysis

To identify the factors that influence the adoption of improved maize technologies among farmers, probit regression model was adopted. Random utility theory (RUT) formed the basis for modeling the determinants of farmers' level of adoption. The RUT follows the utility-maximization condition, which assumes that rational farmers will select a product only if the product provides him the highest utility given a constraint. Based on this theory, farmers' decision to adopt technology is a problem of choice. McFadden[26] developed the RUT for modeling individuals' behavior based on choices. The utility a farmer derives from a product can be represented as having two components; a utility function of observed characteristics known as the deterministic component of utility and the unobserved component known as the random component. The deterministic

component is exogenous and includes farmers' characteristics and technology characteristics, and a set of linearly related parameters and the random component may result from missing data/variables (omitted variable), measurement errors, and misspecification of the utility function.
This function is specified below:

$$U_j = X\beta + \varepsilon \quad (1)$$

Where,

$X\beta = v$

Where U_{ij} is the maximum utility attainable when alternative j is chosen by consumer i; $X\beta$ is the deterministic component of the utility function, X is a vector of observable sociodemographic and economic characteristics, product-specific factors that influence utility, β is the unknown parameter vector to be estimated, and ε is the stochastic term.

The probit regression model

The probit model was used to estimate determinants of adoption of improved maize technology. Probit model is appropriate for modeling dichotomous dependent variable (adoption) which takes value one for high adopters (if a farmer adopts more than half of the 14 production recommendations constituting the improved maize technology) and zero for low adopters (if a adopts less than half of the 14 production recommendations of the improved maize technology).
Another important discrete model is the logit regression model which produces similar results as the probit model.[27,28] The difference between logit and probit models lies in this assumption about the distribution of the errors. The logit model has a standard logistic distribution of errors where the probit model has a standard normal distribution of errors.[28] Again, the estimated parameters in the probit results are between 50% and 60% smaller in absolute value than the corresponding parameter estimates in the logit results.[28]
However, then the choice of employing the probit model for the analysis was based on its realistic standard normal distribution of errors. The probit model assumes that there is a latent continuous variable that determines the value of the observed dependent variable credit specified as

$$y^* = \beta_0 + \sum_{i=1}^{n} x\beta + u_i \quad (2)$$

Where y* is the latent continuous variable, X_i is a set of explanatory variables assumed to influence adoption, β_i is a vector of unknown parameter to be estimated, and u_i is the statistical noise assume to be normally and independently distributed with a zero mean and a constant variance. The method of estimation of the probit model was by maximum likelihood and interpretation of probit results was based on marginal effects treated as probabilities, which explains the slope of the probability curve relating one explanatory variable to prob(y=1|x), holding all other variables constant.
The observable dependent variable is defined by:

$$y = \begin{Bmatrix} 1 access\ if\ y^* > 0 \\ 0\ no\ access\ if\ y^* \leq 0 \end{Bmatrix} \quad (3)$$

The probit model Y follows the Bernoulli distribution with probability

$$\pi_i = \text{pro by } (=1) = \Phi\ (X\beta) \quad (4)$$

Where π_i is the probability that an individual adopted the improved maize technology, X_i is the explanatory variables, β is the regression parameters to be estimated.
In the probit model, the functional distribution of the error is very important to constrain the values of the latent variable into the desirable property of probability values of 0 and 1. The probit model assumes a cumulative distribution function of standard normal distribution represented by Φ.

$$prob(y=1) = prob(y_i^* > 0) = prob(\beta X + e > 0)$$
$$= prob(e < -\beta X)$$
$$= prob(e < -\beta X)$$
$$= \Phi(\beta X) \quad (5)$$

In the case of the normal distribution function, the model to estimate the probability of observing a farmer adopting the improved maize technology can be stated as:

$$pr\,ob(yi = 1/X) = \Phi(\beta X) = \int_{-\infty}^{\beta X} \frac{1}{\sqrt{2\pi}} \exp\left[\frac{-z^2}{2}\right] \partial z \quad (6)$$

Where
$Prob$ is the probability of the farmer adopting the improved maize technology, X is a vector of the explanatory variables, z is the standard normal variable (z~N (0, δ^2)),and β is a k by 1 vector of the Coefficients estimated.
Therefore, the Empirical Probit model is specified in the following form:

$$LV_i = + \beta_0 + \beta_1 X_1 + \beta_2 X_{2i} + \beta_3 X_{3i} + \beta_4 X_{4i} + \beta_5 X_5 + \beta_6 X_{6i} + \beta_7 X_7 + \beta_8 X_8 + \beta_9 X_9 + \beta_{10} X_{10} + \beta_{11} X_{11i} + \beta_{12} X_{12i} + \beta_{13} X_{13} + Ui$$

Definition of variables used in the model is shown in Table 1.

Table 1: Variable used in the model

Variable		Description	Hypothesized sign
Dependent variable			
LV_i	Level of adoption	Dummied as 1 if adopted more than half of recommendation and 0 otherwise	
Explanatory variables			
X_1	Age	In years	±
X_{2i}	Sex	Dummied as 1 if male and 0 if female	±
X_{3i}	Marital status	Dummied as 1 if married and 0 otherwise	+
X_{4i}	Literacy	Dummied as 1 if have can read and/or write and 0 otherwise	+
X_5	HH Size	Number of persons in a household	+
X_{6i}	Member of FBO	Dummied as 1 if belongs to FBO and 0 otherwise	+
X_7	Experience	In years of farming maize	+
X_8	Farm size of maize	In acres	±
X_9	Farm size others	In acres	-
X_{10}	HH annual income	In GHC	+
X_{11i}	Access to labor	Dummied as 1 if have full access to labor and 0 otherwise	+
X_{12i}	Access to credit	Dummied as 1 if ever taken loan for farming and 0 otherwise	+
X_{13}	Extension contact	Number of extension visits received in a seasons	+

Source: Author, 2017

RESULTS AND DISCUSSION

This section presents the result and discussion of the analysis of data gathered for the study. It presents results and discussion on level and determinants of adoption of the various production recommendations in the package of improved maize technology.

Levels of adoption of improved maize technologies

Common improved maize technologies that have been disseminated to farmers include the use of improved and certified seeds; improved land preparation including zero tillage, ridging and harrowing; planting spacing and appropriate planting distance; timely weed control including use of weedicides and mechanical control; and recommended rates of chemical fertilizer application including deep placement. Others included appropriate harvesting and post-harvest management; improved storage facilities as well as crop insurance. However, crop insurance had been recently introduced under Ghana Agricultural Insurance Pool.

Information gathered from the department of agriculture in the Bawku West District Assembly and collaborated by NGOs working to improve agriculture in the district revealed that the package of improved maize technology being disseminated contained 14 production recommendations. To assess the level of practice of the various production recommendations, respondents were asked to indicate the extent to which they follow the production recommendations in their farming activities. The responses were collected on a three-point Likert type scale as "1" if respondent always follows the recommendation, "2" if respondent sometimes fellow the recommendation, and "3" if respondent never follows the recommendation. For each of the 14 production recommendations, respondents were required to indicate the extent to which they follow them in their maize farming activities. Farmers who always practiced the production recommendation were classified as adopters since adoption is the continued use or application of innovation.[17] However, those who occasionally or never practiced a given production recommendation were classified as non-adopters.

All the 400 farmers interviewed were found to be practicing at least three production recommendations out of the 14 production recommendations constituting the improved maize technology disseminated to them. Farmers who were practicing more than half of the 14 production recommendations were regarded as high adopters while those practicing less than half were regarded as low adopters.

Based on this criterion, about 44% of farmers were found to have adopted more than half of the production recommendations and as such were regarded as high adopters, while 56% adopted less than half of the production recommendation and hence classified as low adopters. Thus, the majority of farmers in the district were still low adopters improved technology in their maize production. Salifu and Salifu[29] found the poor level of adoption of improved maize varieties among farmers in the Wa Municipality of the Upper West region. Furthermore, Singha and Baruah[30] found that farmers were poor in the adoption of recommendations of those relatively complex practices in nature such as seed treatment, application of manure and fertilizers, and plant protection measures under different farming systems.

Determinants of level adoption

Based on RUT and Davis[15] TAM, 13 explanatory variables ranging from the socioeconomic characteristic of farmers to farm attributed were entered into the regression analysis. The dependent variable is level of adoption which was measured as a binary variable, dummied as "1" if high adopter and "0" otherwise. Descriptive statistics of the variables used in the probit regression are shown in Table 2.

As shown in Table 2, the average age of farmers was 42.6 years (SD = 10.36), while only 25% of the respondents being female. Average household size was found to be 9 persons per household with only 31% of the farmers being able to read and/or write. Average farm size of maize was 11.7 acre (SD = 4.9) compare with that of other crops being 4.7 (SD = 1.6). Furthermore, average years of experience for cultivating maize were found to be 20 years (SD = 9.95), with that of annual household income being GHS 9329.33. Average extension contact (extension agent visits) was found to be 4 times per season [Table 2].

Table 2: Descriptive statistics of variable used in the model

Variable	Mean±SD
Level of adoption	
Dummied as 1 if adopt more than half of the production recommendations and 0 otherwise	0.44±0.50
Age	
In years	42.60±10.36
Sex	
Dummied as 1 if male and 0 if female	0.75±0.43
Marital status	
Dummied as 1 if married and 0 otherwise	0.88±0.02
Literacy	
Dummied as 1 if have can read and/or write and 0 otherwise	0.31±0.46
HH size	
Number of persons in a household	8.90±4.01
Member of FBO	
Dummied as 1 if belongs to FBO and 0 otherwise	0.27±0.44
Experience	
In years of farming maize	20.16±9.95
Farm size of maize	
In acres	11.71±4.88
Farm size others	
In acres	4.67±1.57
HH annual income	
In GH C	9329.33±15773.86
Access to labor	
Dummied as 1 if have full access to labor and 0 otherwise	0.49±0.50
Access to credit	
Dummied as 1 if ever taken loan for farming and 0 otherwise	0.42±0.47
Extension contact	
Number of extension visits received in a seasons	4.11±2.63

Source: Analysis of field survey data, 2016

Coefficient of determinants of the level of adoption

Table 3 presents the coefficients of regression of probit regression, while that of Table 4 shows the marginal effects of the probit regression. The regression model was found to be significant (1%) with Log likelihood −174.59856; LR $\chi^2(13) = 190.71$ ($P > \chi^2 = 0.0000$). Furthermore, with Pseudo $R^2 = 0.532$, implying that about 53% of the variation in farmers' level of adoption is jointly explained by the explanatory variables used in the model.

Out of the 13 variables entered into the model, nine variables were found to be significant in determining farmers' level adoption. The significant variables were age, sex, household size, experience in farming maize, and maize farm size. The others were household annual income, access to labor, access to credit, and extension contact.

These findings are similar to Salifu and Salifu[29] who found age, marital status, education of household head, and farmers' experience as significant determinants of adoption of improved maize in the Wa Municipality, Similarly Fadare *et al.*[31] also found farm size, education level of farmers and access to extension services to as significant determinants of adoption of improved maize technologies. Furthermore, Singha and Baruah[30] found that extension contact, annual income, innovation proneness, and positive

Table 3: Coefficients of probit regression

Variable	Coefficient	Standard error	Z
Age	−0.2782659***	0.0994818	−2.80
Sex	0.6151916***	0.1856908	3.31
Marital status	0.0667152	0.1126562	0.59
Literacy	0.1595935	0.1709878	0.93
HH size	0.0530352**	0.0229694	2.31
Membership of FBO	−0.0214121	0.1946384	−0.11
Experience	0.5312992***	0.1971204	2.70
Farm size of maize	0.0529868***	0.0092625	5.72
Farm size others	−0.0290108	0 0.0500002	−0.58
HH annual income	5.9434612***	0.1418081	4.80
Access to labour	0.3590858**	0.1634473	2.20
Access to credit	0.4228778***	0.151048	2.80
Extension contact	0.1286375***	0.0250573	5.13
_cons	−2.484537	0.5102143	−4.87
Number of obs.	395		
Log likelihood	−174.59856		
LR χ^2 (13); P>χ^2	190.71		
Pseudo R^2	0.532		

Source: Analysis of Field survey data, 2016

Table 4: Marginal effect of probit regression

Variable	dF/dx	Standard error	Z
Age	−0.0935048***	0.024386	−2.80
Sex	0.1849917***	0.0541277	3.31
Marital status	0.022418	0.038105	0.59
Literacy	0.0545048	0.0601424	0.93
HH size	0.0178212**	0.007897	2.31
Member of FBO	−0.0071735	0.065029	−0.11
Experience	0.1785308***	0.0488378	2.70
Farm size of maize	0.0178049***	0.0036772	5.72
Farm size others	−0.0097484	0.0168368	−0.58
HH annual income	0.3067896	0.0639145	4.80
Access to labour	0.1208992**	0.056116	2.20
Access to credit	0.1420979***	0.053497	2.80
Extension contact	0.0432256****	0.0094325	5.13
Number of obs.	395		
Log likelihood	−174.59856		
LR χ^2 (13); P>χ^2	190.71		
Pseudo R^2	0.532		

Source: Analysis of field survey data, 2016

attitude toward farm diversification of farmers had positive significant relationships with the extent of adoption of improved cereal cultivation practices. However, marital status, literacy, membership of FBOs, and farm size of other crops were found not to be significant determinants of farmers' level of adoption.

Age of farmers was found to be significant at <1% level of significant and negatively related to farmers' level of adoption of improved maize technology [Table 3]. This implies that age significantly affected farmers' level of adoption. The negative sign of the coefficient of the variable "age" indicates a negative relationship. Thus, younger farmers are more likely to adopt higher production recommendations in the improved maize technology compared with older ones. Furthermore, as shown in Table 4, the marginal effect of variable "age" is 0.024. This implies that one unit increase in respondents' age will induce a reduction of 2.4% in the probability of a respondent being a high adopter.

Sex of respondents (measured as dummied; "1" if male or "0" otherwise) was found to be significant (at <1% level of significant) in determining farmers' level of adoption of improved maize technology. Sex was positively related to the level of adoption, indicating that male farmers were more likely to be high adopters compared with their female counterparts. As shown in Table 4, the marginal effect of the variable sex on the level of adoption is 0.185. This illustrates that the difference in probabilities between varying the variable sex to 1 and setting it to 0, given that all other explanatory variables are set at their sample means, increases the likelihood of male farmers being high adopters by 18.5%. This implies male farmers are 18.5% more likelihood to adopt the majority of the production recommendations than female farmer.

Furthermore, household size was found to be significant at 5% in determining farmers' level of adoption [Table 3]. The positive sign of the variable household size indicates that larger households are more likely to adopt more production recommendations (high adopters) compared with the smaller household. This was expected due to the labor intensive nature of the improved maize technology. In the study area farmers largely depend on members of their household for their farm labor requirement. As such larger households are more likely to adopt the improved maize technology. As shown by the marginal effect [Table 3], one-unit increase in household size will increase the probability of respondent being classified as a high adopter by 1.8%.

Experience in maize farming, measured as the number of years a farmer is engaged in maize farming, was also found to be significant (1% level significant) and positively related to the level of adoption of improved maize technology [Table 3]. Thus, farmers who are more experienced in maize farming are more likely to be high adopters than less experienced ones. Furthermore, increasing a farmer's experience by 1 year will increase the probability of the farmer being high adopter by 17.8% all other things being equal.

Similarly, farm size was also found to be positive and significant (at <1% level of significant) with the level of adoption [Table 3]. This implies that farmers with larger farms were more likely to have adopted more production recommendations than farmers with small farm holdings. This was least expected due to the labor intensive nature of the technology. This is because farmers with large farm holding will need more labor to practice many of the production recommendations such planting in line with the recommended spacing, recommended fertilizer application method, and recommended time for weed control among others. As shown by the marginal effect, one-unit increase in farm size will induce 17.5% increase in the probability of a farmer being a high adopter.

Household annual income was found to be significant at <1% and positively related to the level of adoption [Table 3]. This means respondents with high household annual income were more likely to be high adopter. This was anticipated because adopting most of the production recommendations demand some expenditure of cash resources. Therefore, household with more income will be able to purchase fertilizer, improved and certified seeds, hire labor and other inputs to practice more of the production recommendations. With a marginal effect of the variable "household annual income" being 0.31 [Table 4], it means that one-unit increase in household annual income will induce about 31% increase the probability of the farmer being a high adopter.

As shown in Table 3, the probit analysis identified access to credit as significant at <1% and positively related to the level of adoption of the improved maize technology. This implies that respondents who reported to have taken credit to invest in their maize farms were found more likely to be high adopters than reverse. With the marginal effect of the variable "access to credit" being 0.14, implies that, varying the variable access to credit from "0" to "1" will increase the probability of a respondent being high adopter by 14.2%, holding all other variables at their sample mean level.

As expected, farmers' access to labor was found to be significant at 5% level of significant and positively related to the level of adoption of the improved maize technology. Thus, farmers' with high access to labor were found to be more likely to adopt more of the production recommendations. With the marginal effect of the variable "access to labor" being 0.12 as shown in Table 4, implies that varying the variable "access to labor" from "0" to "1" will increase the probability of a respondent adopting more of the production recommendations and as such being high adopter by about 12%.

Extension contact measured as the number of extension agent visits or contact for the purpose of agricultural information dissemination within a production season was found to be significant at <1% and positively related to the level of adoption. Thus, farmers with more extension contacts are more likely to adopt many production recommendations. The marginal effect of "extension contact" is 0.043 [Table 4] indicating that, if there is one-unit increase in extension contact, the probability of the said farmer being high adopter will increase by 4.3%.

CONCLUSION AND RECOMMENDATIONS

Close to half (44%) of the 400 farmers surveyed in this study followed more than half of the 14 production recommendations in the improved maize technology package being disseminated in the district. Sex, access to credit, labor, and extension contact were found as significant determinants of farmers' level of adoption of the improved maize technology.

Level of adoption of the improved technology among female farmers was found to be low compared with their male counterparts, due to female farmers generally lacked access to extension services and information on the improved maize technology. Furthermore, farmers who were able to access, labor, and extension service were more likely to practice more of the production recommendations. It is, therefore, recommended that extension service should consider gender concerns and mainstream these concerns in their service delivery. This will ensure that both men and women farmers have equal access to agricultural information. The study recommends to MOFA to promote the use of labor saving simple farm tools in carrying out the various production recommendations under the improved maize technology. Furthermore, MOFA needs to work with financial institutions to support maize farmers in the district with credit to enable them to acquire the necessary inputs required in the implementation of the improved maize technology.

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