Determinants of Farmers Adoption of Improved Maize Varieties in the Wa Municipality

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Abstract

This paper examines determinants of farmers' adoption of improved maize varieties (IMVs) in the Beehi and Kpongu communities of the Wa municipality in the Upper West Region of Ghana. The analysis involved a cross-sectional survey with 300 systematic sampled household heads growing maize in the two selected communities. A binary logistic model was fitted to examine the determinants of adoption. Both exploratory and confirmatory factor analysis was used to select influential variables in to the logistic model. Results from factor analysis indicates that, six factor solution which accounts for 68.85% of the total variance was appropriate and adequate in explaining why differences exist in the choice of improved maize varieties among the farmers. The logistic analysis shows that age, marital status, education of household head,farmers' experience in maize production and varietal characteristics were the most significant (P<0.05) factors that influenced adoption improved maize varieties. Predictors such as farm labor, extension services and belonging to farm organization did not show significant (P>0.05) influence on adoption of IMVs contrary to common beliefs and earlier empirical results. To improve food security of small-holder farmers in the Wa municipality agricultural extension should strengthen farmers' knowledge and positive attitudes toward improved maize varieties through educational campaigns and on-farm trials. It is also important that, researchers in maize breeding should Chanel efforts towards developing varieties with wide adaptation.

Keywords: Adoption, Logistic analysis, Cross-sectional, Upper West, Factor analysis, influence

1. Introduction

Maize has been cultivated in Ghana for several hundred years. After being introduced in the late 16th century, it soon established itself as an important food crop in the southern part of the country. Early on, maize also attracted the attention of commercial farmers, although it never achieved the economic importance of traditional plantation crops, such as oil palm and cocoa. Over time, the declining profitability of many plantation crops as a result of increasing disease problems in cocoa, deforestation and falling world commodity prices served to strengthen interest in commercial food crops, including maize. Today, maize is Ghana's most important cereal crop. It is grown by the vast majority of rural households in all parts of the country as in other African countries; maize is cultivated by both men and women. Ghana is by far different from many other countries in that, women frequently manage their own maize fields, contribute an important proportion of the overall labour requirements, and exercise complete discretion over the disposal of the harvest (Morris et al., 1998). For all these achievements, major technological challenges and yield gaps persist in Ghana. Staple crops such as maize and rice, yields are generally less than half of economically attainable yields (MOFA. 20011).

For example, national average yields range between 1.7 metric tons/hectare1 and 2.5 tons/hectare for maize and rice respectively (MOFA. 1993 – 2011); meanwhile, data from different on-station and on-farm trials suggest that yield averages of 4 to 6 tons/hectare for maize and 6 to 8 tons/hectare for paddy rice are achievable (MOFA/CRI/SARI. 2005). These figures show a huge gap between actual and achievable yields and, at the same time, a window of opportunity to close that yield gap and increase productivity. Since independence, 56 years ago, agriculture has continued to play a central role in the livelihoods of Ghanaians. It used to employs about 56% of the population and accounts for 28.3% of Gross Domestic Product (GDP), but now employs 42% of total workforce and contributes 22.7% to GDP in 2012 (GSS., 2010). Maize is one of the important food crops grown in all the ecological zones of the country. However, the cultivation and production differs in these ecological zones. Between 2011 and 2012 about 1,042 hectares of land area allocated to cereals was planted with maize (SRID.MOFA. 2012). Maize has recently surpassed cassava as Africa's most important food crop in terms of calories consumed (Webb and E. D. Highly, 2000) and also doubles as a main source of income for the producers in the maize surplus regions. Maize also determines a household food security such that a low-income household is considered food insecure if it has no maize stock in store, regardless of other foods the household has at its disposal (Tweneboah, C. K., 2000).

Ghana is been regarded as an African success story as a result of its impressive achievements in accelerating growth and reducing poverty and hunger in line with the Millennium Development Goals. There is a strong agricultural output growth about 9.02% annually from 2010to 2012 (SRID. MOFA, 2012) has played an important role in this development. However, much of the growth has been through expansion of cultivated area and not through total-factor-productivity growth, which has averaged only 1.2 percent annually—higher than the African average of 0.5 percent, but well below the global average of 1.8 percent in the 2001–09 periods (Fuglie, K., 2012).

Increasing agricultural productivity and hence production using the improved agricultural technologies is a precondition for achieving food security in Ghana without food aids. As long as farmers continue to use traditional low yielding crop varieties, agricultural productivity will remain low. Small-scale farmers in the Wa Municipality who depends mainly on agriculture have the potential to improve their welfare if they adopt improved production technologies. Efforts have therefore been made by various national and international research institutes to develop improved crop technologies for use by farmers. Ghana has a potential for increasing the production of maize in the guinea savanna zone of the country especially in Wa. However, it has been observed that despite the efforts made by the government and the Ministry of Food and Agriculture particularly through the introduction of new varieties of maize, the productivity of maize on farmers' fields is generally low, averaging 1.55mt/ha (PPMED, 1991 and 1998). The existing low levels of productivity in maize could be attributed to low level of adoption of maize technologies. This current paper therefore seeks to identify and describe the major variables (factors) that underlie Adoption of improved Maize Varieties and build a model for predicting farmer's attitudes.

2. Materials and Methods

This study involved a cross-sectional survey with 300 systematic sampled households growing maize in the two selected communities of Biihii and Kpongu in the Wa Municipality of the country. The Wa Municipality is one of the nine administrative areas (District Assemblies) that make up the Upper West Region (UWR) of Ghana. Despite the Municipality been the commercial hub of the region; agriculture is the main economic activity. It remains the largest single contributor to the local economy and employs about 70% of the active population [5]. The main staple crops grown include millet, sorghum, maize, rice, cowpea, and groundnut cultivated on subsistence basis. Biihii and Kpongu were selected purposely because of the importance of maize in the farming systems and the availability of maize technology dissemination programs in the two areas. . A questionnaire was administrated through a face-to-face interview of 135 households from Kpongu and 165 households from Beehii.

2.1 Organization of Data

The following attributes of the improve varieties were explored using a 5- points Likert scaled with 1= Not at all, 2= A little, 3 = moderately, 4 = quite a bit, 5 = extremely. Factor analysis was then applied to the resulting continuous responses of these variables.

These variables were as follows: 1.High yield, 2.Availability, 3.Storage/streak resistance, 4.Often expired 5.Mature late, 6.Weed resistance, 7.Bad quality (Grain color/texture), 8.Low yield, 9.Can withstand water stress, 10.Taste/cooking quality (Nutrition), 11.Mature early, 12.Require too much fertilizer, 13.Lack information on how to use, 14.Diseases/pest resistance, 15. Can do better under poor soil, 16.Cost.Each item on likert scale indicates the extent to which the farmer feels it affect his/her choice/use of the variety (ies), with one (1) denoting no effect and five (5) been higher effect. The Independent variables used in the study were some selected attributes of the IMVs and socio-economic characteristics of farmers that were hypothesized to influence adoption of farm technologies according to literature. The socio-economic characteristics of the farmers included age, education l status, gender, marital status, contact with agricultural extension, location (community) of the farmer, farm labour, farmers experience in maize production farmers belongings to Farmer Base Organization (FBO). The technology characteristics included influential variables in the final factor solution.

2.2The Factor Model

Principal component factoring was the method to performing the factor analysis. In order to determine the latent factors underlying the correlations among p variables, the correlation matrix of the indicator variables was subjected to principal component analysis. This technique allows each of the p possible principal components (f_i), be expressed as a linear combination of the original variables (X_i) as

$$f_i = \sum_{j=1}^{p} a_{ij} X_j \quad (1)$$

Where the set of coefficients, a_{ij}(j = 1,2, ...,P) is the eigenvectors of f_i . Equation (2.1) could be written such that, the principal component scores are standardized to have a unit variance. Denoting the eigenvalue of the component $(fi)$by αi, then fi accounts for an amount or αi of the variation in the data. Then Var($\frac{fi}{\sqrt{\alpha i}}$)= 1 and $\frac{fi}{\sqrt{\alpha i}}$ is a standardized principal component. Equation (2.1) can be then written as

$$fi = \sum_{j=1}^{p} \beta ijXj \quad , \quad \beta ij = aij\sqrt{\alpha i} \qquad (2)$$

Where $fi = \sum_{j=1}^{p} \beta\, ij$ is the eigenvalue of fi and ($\beta ij, j = 1,2, \dots p$) is the vector of factor loadings of f_i on the variables. The matrix alternative of Equation (3.2) is $f = \wedge^1 X$ (3)
Where f is a p x 1 vector of standardized components.

$\wedge$ is a p x p orthonormal matrix of factor loadings;
X is a p x 1 vector of indicator variables.
Thus,$\wedge\wedge'$ = l is a p x p identity matrix, and from Equation (3)

$$X = \wedge f \qquad (4)$$

Equation (3.4) expresses each original variable X_j, as a linear combination for the principal components. This Equation is to determine the smallest number of factors that need to be retained in the factor solution. There are a number of techniques use in factor extraction which include the following (Pallant J., 2002).The Kaiser's criterion, which is one of the most popular used technique, also known as the eigenvalue rule was used for this study. For this rule, only factors with eigenvalue of 1.0 or more are retained.

2.2 The Logistic Model

In the field of agriculture, adoption of technologies is measured as a dichotomous response variable (0 = non -adoption of innovation and 1= adoption of innovation. The logistic model is the standard method of analysis, when the outcome variable is dichotomous (Hosmer and Lemeshow, 2000). The logistic regression model is used in this study to predict the relative likelihood of adoption of IMVs by farmers. The goal of logistic regression is to identify the best fitting model that describes the relationship between a binary dependent variable and a set of independent or explanatory variables. The dependent variable is the population proportion or probability (p) that, the resulting outcome is equal to 1(one). Parameters obtained for the independent variables can be used to estimate odds ratios for each of the independent variables in the model. For the binary response variable y, denotes its categories by 1 and 0. It uses the generic term success and failure for the two outcomes. According to Agresti, (2007)., logistic regression is the most preferred where the independent variables are categorical or mix of continuous and categorical. In this study, we code $y=1$ (adoptor) and $y=0$(non-adoptor).

The specific form of the logistic regression model is:

$$\pi(X) = p = \frac{e^{\beta_0 + \sum_{i=1}^{n} \beta_i x_i}}{1 + e^{\beta_0 + \sum_{i=1}^{n} \beta_i x_i}} \quad (5)$$

However, the logit transformation of the odds, or likelihood ratio that, dependent variable is 1, such that;

$$\operatorname{logit}(p) = In\left(\frac{p}{1-p}\right) = \beta_0 + \sum_{i=1}^{n} \beta_i \cdot x_i \quad (6)$$

Where

β_0 : The model constant

β_i : The parameter estimates for the independent variables.

x_i : The set of independent variables (i =1, 2… n)

p : Probability ranges from 0 to 1

$In\left(\frac{p}{1-p}\right)$: The natural logarithm ranges from negative infinity to positive infinity.

According to Peng et al. (2002).there are two important reasons that make logistic regression popular;

1. The range of the logistic function is between 0 and 1; that make it suitable for use as probability model, representing individual risk.
2. The logistic regression curve has an increasing s-shape with a threshold; that makes it suitable for use as statistical model, representing risk due to exposure.

The fundamental equation for the logistic regression shows that when the value of an independent variable increases by one unit, and all other values are held constant, the new probability ratio $\left[p/(1-p)\right]$ is given as follows:

$$In\left(\frac{p}{1-p}\right) = \exp^{\beta_0 + \sum_{i=1}^{n} \beta(x_i+1)} = \exp^{\beta_0} .\exp^{\sum_{i=1}^{n} \beta_i . x_i} .\exp^{\sum_{i=1}^{n} \beta_i}$$

$$Logitp(x) = \alpha + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k \quad (7)$$

Thus, the logit of p(x) simplifies to the linear sum.

The quantity p(x) divided by 1-p(x), whose log value gives the logit, describes the odds for a malaria patient being dead, with independent variables specified by x.

$$\frac{p(x)}{1+p(x)} = \text{odds} \quad (8)$$

for individual x.

3. Results and Discussions

Descriptive analyses of households in the study areas are shown in table 1. The results reveal a high illiteracy rate (59.7%) for the sampled farmers, with about 23% of them having some formal education. The table also shows that most of the households were male-headed (87.3%) and had married heads (89.7%). Although more than half of the households participated in local farmer based organizations, only 17.7% accessed credit in the 2013/14 season. On the average a household size was composed of 9 persons with actual farm labour comprising 5 persons headed by a 40 year old adult. Farmers in the study area had higher experience (about 10 yeas) in improved maize production. Seven (7) out of the twenty-seven improved maize varieties were found to be cultivated in the study areas. Obatanpa, Mamaba and Aburohemaa (34%, 20.7% and 16.3%) respectively were found to be most popular among the farmers in the study areas.

In order to identify the major factors that underlie the choice of improved maize varieties in the communities both exploratory and confirmatory factor analysis was used to select influential variables in to the logistic model. Results from factor analysis indicates that, six factor solution which accounts for 68.85% of the total variance was appropriate and adequate in explaining why differences exist in the choice of improved maize varieties among the people of Beehii and Kpongu communities. The Factors are general "quality factor" of the variety, "weed resistant factor", "storage/streak resistant factor", the "maturity factor", the diseases resistant factor and the "re-propagation (Recycling) factor". Collinearity diagnostic in Multiple Logistic Regression reveals no serious correlation among the variables. Most of the Variance Inflation Factor (VIF) estimates had values less than 2, which indicate no serious problems of collineraity.

Table 3 present the maximum likelihood estimates of the logistic models for factors influencing adoption of improved maize varieties. The fit of the models was satisfactory. The estimated coefficients for the likelihood ratio chi-square were Significant ($P<.000$), with chi-square values of 126.082. The models accounted (R2 Logistic.) for 54.6% of the variation between adopters and non-adopters of improved maize. This indicates that the test of dependence of adoption of IMVs on the explanatory variables. The model estimation also shows that the covariates were all associated with the log odds of IMVs adoption. The hypothesis that all the variables can be dropped from the model was rejected at 1% level significance since the Wald statistic was 93.863 ($P<0.000$). Nine variables included in the model were statistically significant at 5% level in explaining farmers adoption of IMV's in the study areas. In terms of farmers characteristics, location and gender did were not significantly associated with adoption of IMVs. This result is consistent with (Morris et al., 1998 and De Groote et al., 2002). Contrary to this (Thomson et al., 2014) reported that sex of the household head matters in explaining adoption of improved maize varieties with adoption favoring male-headed households. The insignificant value of location on adoption of IMVs probably reflects the fact that either communities (Beehi or kpongu) are in the same municipality and thus possesses similar climatic conditions.

Age however, has significant influence on IMVS adoption which is negatively associated with the log odds of adoption of IMVs. This indicates that adopters of IMVs were younger than the non-adopters. Previous studies however showed inconsistent results of age effect on adoption of improved maize varieties. Some researchers reported non-significant influence of age on adoption of IMVs (PPMED, 1998,Paudel and Matsuoka, andAlene,, and Mwalughali. 2012) while (Kaliba et al., 2014 and Ensermu et al., 1998) showed a strong positive association between age and adoption of improve varieties. In line with the current study,(Morris et al., 1998,Fufa and Hassan, 2006, Thomson et al., 2014 and Bashir and Wegrary 2014) found negative influence of age on adoption. The result as expected also shows education to be significantly influencing IMVs adoption where households with no education are less likely to adopt new technologies. This finding is consistent with previous studies such as (Tura et al., 2010, Thomson et al., 2014 and Feleke and Zegeye., 2005) who reported significant influence of education on adoption of IMVs. For this study, every single year of no formal schooling decreased adoption of IMVs by 36%. Experience in maize production had a significant influence on adoption of IMVs. The logit results show that the probability of adoption of improved maize varieties is directly related to years of the farmers' exposer to maize production. One more year of maize production, the household probability of adopting improved varieties by 13.5%. Interestingly, predictors such as farm labour, extension services and belonging to farm organization did not show significant influence on adoption of IMVs as reported other investigators such as (Kaliba et al., 2000 and Paudel and Matsuoka, 2008).

Considering the attributes of improved maize varieties, attributes such as grain quality (Grain color/texture) Low yield, Can withstand water stress, require too much fertilizer, Lack information on how to use were significantly influencing adoption of IMVs. This implies that a unit improvement in the quality (grain color/texture) of maize would increase adoption of INMVs by 19.93%. Also, adoption of IMVs is expected to decrease by 42.2%, 29.6%, and 26.9% for every unit reduction of yield, water resistance and information services respectively. However, adoption of IMVs is decreased by 47.7% for every additional fertilizer used. These results are in line with the findings of (Kaliba et al., 2000) who reported that these factors had significant influence on adoption of IMVs.

4. Conclusions

This work examined the determinants of adoption of improved maize varieties in the Wa municipality of the Upper West region of Ghana. The study was carried out in two selected communities, namely Beehi and Kpongu, where improved maize variety studies are rarely done.

Factors influencing adoption of IMVs considered in the study were farmer's socio-demographic characteristics, institutional and environmental factors as well as attributes of improved maize varieties. A number of factors were found to influencing the adoption of IMVs. Age, marital status and educational status of household head substantially influence adoption of IMVs. The results of this current study contradict many empirical results which held the belief that extension visits and household labor has positive effect on adoption of IMVs. This could be the fact that extension workers in the study area were not promoting the production of IMVs or their frequency of visits is low. The results suggest that farmers in the study area seek specific varietal attributes, such as grain quality, yield potential, tolerance to water stress, reasonable fertilizer application and information on how to use. The finding of farmer perceptions of technology-specific characteristics significantly condition technology adoption decisions is consistent with recent evidence in literature, which suggests the need to go beyond the commonly considered socio-economic, demographic and institutional factors in adoption modeling (Feder et al., 1985; Feder and Umali, 1993).

The results of this study are useful in policy design strategies or interventions that will assist in increasing the adoption and utilization of improved maize varieties among smallholder farmers. Adoption of IMVs will help to increase agricultural productivity and hence improve food security in Ghana especially in the Wa municipality. For instance, the findings on farmer characteristics and membership to organizations have important policy implications in which agricultural extension workers should intensifies visits to small-holder farmers. Finally, considering the factors affecting the adoption of IMVs, research institutions and extension service department of the ministry of food and agriculture needs to react and pursue proactive measures of providing improved maize varieties to smallholder farmers.

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Table 1: Characteristics of Household Heads

Variables	Frequency (n = 300)	Percent
Location (Community)		
Beehii	165	45
Kpongu	135	55
Gender		
Male	262	87.3
Female	38	12.7
Educational Status		
Illiterate	269	59.7
Some Formal School	31	23
Non-Formal School	52	17.3
Marital Status		
Married	269	89.7
Divorced	15	5
Widowed	9	3
Single	7	2.3
Extension Visits		
Yes	259	86.3
NO	41	13.7
Belongings to FBO		
Yes	206	68.7
No	94	31.3

Table 2: Final factor Solutions

Indicators	Component					
	1	2	3	4	5	6
Variable 12	0.862*					
Variable 5	0.738*					
Variable 8	0.722*					
Variable 7	0.678*					
Variable 16	0.637*		-0.554			
Variable 13	-0.574					
Variable 6		0.780*				
Variable 15		-0.682				
Variable 10	-0.407	-0.630		-0.408		
Variable 11			0.836*			
Variable 9	-0.464		0.658			
Variable 3				0.888*		
Variable 14					0.728*	
Variable 1					0.568	
Variable 4						
Variable 2						0.800*
						0.622

*Influential Variables

Table 2: Logistic Regression Predicting Likelihood of IMVs Adoption

Variables in the Equation

Variables	B	S.E.	Wald	Df	Sig.	Exp(B)	95% C.I.for EXP(B)	
							Lower	Upper
Location	1.126	.855	1.734	1	.188	3.082	.577	16.467
Gender	-1.558	.851	3.350	1	.067	.211	.040	1.117
Age**	-.144	.075	3.655	1	.046	.866	.747	1.004
Edustatus*	-3.325	1.158	8.247	1	.004	.036	.004	.348
Maristatus*	-7.841	1.671	22.019	1	.000	.000	.000	.010
Extension	-.708	1.141	.385	1	.535	.493	.053	4.612
Farmorg	-1.548	.894	2.996	1	.083	.213	.037	1.227
Street _Resist	.456	.559	.666	1	.415	1.577	.528	4.713
Recycle_grain	.282	.252	1.248	1	.264	1.326	.808	2.173
Late_maturity	-.804	.444	3.282	1	.070	.447	.187	1.068
Weed_Resist	.794	.664	1.428	1	.232	2.212	.602	8.128
Grain_quality**	.690	.320	4.648	1	.031	1.993	1.065	3.730
Low_yield	-.840	.307	7.503	1	.006	.432	.237	.788
Waterstres-Re*	-1.218	.399	9.315	1	.002	.296	.135	.647
Early_maturity	-.255	.260	.969	1	.325	.775	.466	1.288
Fert_Requirnt*	-.741	.317	5.475	1	.019	.477	.256	.887
Info_Available*	-1.314	.357	13.561	1	.000	.269	.133	.541
Dese/pest_Rest	.350	.347	1.015	1	.314	1.419	.718	2.801
Cost	.039	.401	.010	1	.922	1.040	.474	2.285
Tlabour	-.116	.204	.325	1	.569	.890	.596	1.329
Maize_exp*	.304	.119	6.541	1	.011	1.355	1.074	1.711
Constant*	16.185	4.748	11.622	1	.001	10694141.517		

**, * Indicate marginal and statistical significance at 5%.