

# **Effect of socio-economic factors on level of use of improved maize varieties in Bungoma County, Kenya**

## **Abstract**

Maize is Kenya's primary staple food, where 75% of producers are smallholder farmers. Maize consumption exceeds production with imports bridging the gap. Improved maize varieties have been adopted by smallholder farmers but the deficit gap still exists. The study's objective was to determine factors influencing the adoption intensity of improved maize varieties in Bungoma County. Primary data was collected from 500 smallholder farmers using a structured questionnaire. Data was analysed using the Statistical Package for Social Scientists software and a fractional logit model applied. Factors influencing adoption intensity of improved maize varieties were personal characteristics of the farmer (age, and household size), institutional factors (extension service) and varietal factors (early maturity, pest and disease resistance, drought resistance). The recommendations from the study is that the extension service needs to address and manage risk aversion among the old farmers through providing information and support groups. Counties should nurture a strong research-extension linkage where researchers can demonstrate technology benefits.

*Keywords: maize varieties, intensity of adoption, fractional response model*

## **Introduction**

Maize is the primary staple food of ordinary Kenyans, and the cheapest source of calories among the cereal grains. In Kenya, 90% of its population depends on maize as a key staple food crop, with 75% of maize producers being small holder farmers located in low to mid altitude ecologies (Obunyali et al., 2019). According to the Agricultural Sector Transformation and Growth Strategy 2019-2029, maize accounts for about 50% of cereals value, and the maize value chain is one of the crop value chains with the highest potential for agricultural transformation. Among crop farmers, 58% of small-scale farming land is allocated to maize production but only 10-15% of incomes for these farmers come from maize.

Kenya's per capita maize consumption is the highest in Eastern Africa, standing at 103 kg/year compared to 73 kg/year for Tanzania, 52 kg/ year for Ethiopia and 31 kg/year for Uganda. Currently, maize consumption in Kenya outweighs its production, and the former is bound to increase with increase in population. According to (KNBS, 2019) aggregate maize production decreased from 42.1 million (100 Kg) bags (4.21 million metric tonnes-MT) in 2020 to 36.7 million bags (3.67 million MT) in 2021. On the other hand, the volume of imported maize nearly doubled from about 274,000 MT in 2020 to 487,000 MT in 2021. The value of imports from Tanzania nearly doubled

from KES 27.9 billion in 2020 to KES 54.5 billion in 2021 partly attributable to increase in imports of maize and rice from this country.

To bridge this gap, a yield increase of 157% is required (Marenya et al., 2021). Maize production therefore needs to be increased to meet demand and avoid overreliance on imports. A study by Abodi et al., (2022) highlights the perennial maize imports in Kenya and shows that the net effect of maize imports on economic welfare is negative, and asserts that increased domestic production benefits both producers and consumers while facilitating efficient allocation of resources in the maize sub sector.

Improving productivity of maize needs increased efforts in influencing the farmer to use improved maize varieties. In Kenya, maize yield fluctuates from 1.5-1.8tonnes/hectare against a potential of 4.5tonnes/hectare (Marenya et al., 2021). This yield gap highlights the need to increase yield, and one of the ways to do this is through improved technologies such as improved maize varieties. New /improved maize varieties with better genetic gains have been developed and adopted through the years, yet the yield gap still exists. The use of genetically impure seeds hinders the realization of maize yield potential, for instance a one percent decrease in varietal purity could lead to a loss of 135kg/ha in maize production (Srii et al., 2021). This paper highlights the socioeconomics issues around the use of improved maize varieties by farmers in Bungoma County.

### **Literature review**

Many studies have viewed adoption as a binary process when in reality the adoption process is partial and incremental, meaning that it is the levels of a technology that are adopted, and this levels may be increased over time. Past studies have shown that it is important to go beyond mere adoption studies that estimate factors influencing adoption to estimating factors that determine the level (intensity) of adoption of technologies at the household level. This is because various adoption studies have shown that factors determining adoption and those that determine intensity of adoption of a technology can be different. In their study on modeling the adoption and use intensity of improved maize seeds in Benin West-Africa, Mahoussi et al., (2021) identified more factors that influenced intensity of adoption than those that influenced adoption of improved maize varieties in Benin. In their study on determinants of adoption and intensity of improved faba bean cultivars in the central highlands of Ethiopia, Kassa et al., (2021) asserts that the decisions to adopt the improved cultivars and how much land to be covered (intensity of adoption) appeared to be explained by different processes. The decision to adopt improved faba bean cultivars was influenced by family size, farmers' awareness about the existing improved cultivars, and extension contact but the intensity of adoption was determined by livestock holding and access to market information. Kolady et al., (2021) also noted differences in factors affecting adoption and those influencing intensity of adoption of precision agriculture technologies (PAT). In the study on factors influencing adoption of irrigation technologies among smallholder farmers in Machakos County, Kenya, Muluki et al., (2022) found that sex of household head, education, farm size, off-farm income, access

to credit and access to extension services positively influenced adoption while adoption intensity was positively influenced by gender, off-farm income, farming experience, primary occupation and extension services. These studies show that a binary econometric model, which is used in many adoption studies, is not sufficient to highlight the socioeconomic constraints influencing the intensity of adoption of any given technology. The studies therefore underscore the contribution of intensity of adoption studies to adoption studies, and the need to estimate the determinants for the level of adoption of any given technology.

Mahoussi et al., (2021) used the double hurdle Tobit model to identify factors affecting adoption as well as the intensity of adoption of improved maize varieties in Benin. However, the Tobit model is suitable when the dependent variable is bounded on one side. In our study, the dependent variable, which is the proportion of the area devoted to maize production with improved maize seeds is continuous but bounded between 0 and 1. According to (Gallani & Krishnan, 2017), Tobit models rely on distributional assumptions that are frequently not reflected in survey data. For instance, the observations/responses may be skewed on one side of the scale. An assumption of the Tobit model is that zeros in the dependent variable represent censored values of an underlying normally distributed latent variable (Brown & Dunn, 2011), which may not be the case when the dependent variable is the proportion of land under a particular crop. The zero in the latter means that a crop was not grown by the respondent. Kassa et al., (2021) used the double hurdle Tobit model to analyse the decision to adopt faba bean cultivars in the first stage and the area of land under bean (intensity of adoption) in the second stage. Kolady et al., (2021) used the Probit and Poisson regression models for the analysis, where the Probit model was used for the decision to adopt (1) or not to adopt (0) while the Poisson regression model was used where the number of technologies adopted was the dependent variable. Kwawu et al., (2022) also used the Poisson regression model and the dependent variable was the number of improved maize technology package elements adopted by farmers. According to Gallani and Krishnan (2017), the Poisson regression models are appropriate for discrete variables, and where the number of technologies used are many. Pedzisa et al. 2015, in their study on intensity of adoption of conservation agriculture by smallholder farmers in Zimbabwe used the Poisson regression model because the model had eight conservation agriculture practices in the dependent variable. The Poisson regression model may not be appropriate in this study because the dependent variable, which is the proportion of land under improved maize varieties is a continuous variable. Muluki et al., (2022) used the Probit model to analyze the factors influencing the decision to adopt irrigation technologies while the Ordinary Least Squares (OLS) regression was used to analyze the factors influencing the area put under irrigation. According to (Gallani & Krishnan, 2017), the OLS is inappropriate to estimate models of bounded dependent variables because the predicted values may be outside the bounded variables. In addition, the partial effects estimated by OLS regressions are constant and independent of the value of the predictor.

The fractional response model (FRM) on the other hand overcomes many limitations of established linear and non-linear econometric solutions in the study of bounded data. Studies that have estimated the intensity of adoption by use of the FRM include Misango et al., 2022, (Arslan et al., 2014) and (Danso-Abbeam et al., 2017). Misango et al., 2022, used the fractional logit model to analyze the intensity of adoption of integrated pest management practices in Rwanda. The dependent variable was acres of maize under PPT divided by the total acreage under maize per farm. Arslan et al., 2014 used the FRM to estimate the determinants for the intensity of adoption of conservation practices, which was defined as the proportion of land cultivated with conservation practices. In their study on adoption of improved maize varieties among farm households in the northern region of Ghana, (Danso-Abbeam et al., 2017) used the FRM to estimate the factors influencing the intensity of adoption of improved maize varieties, and the dependent variable was the proportion of the total farmland allocated to the cultivation of improved maize varieties.

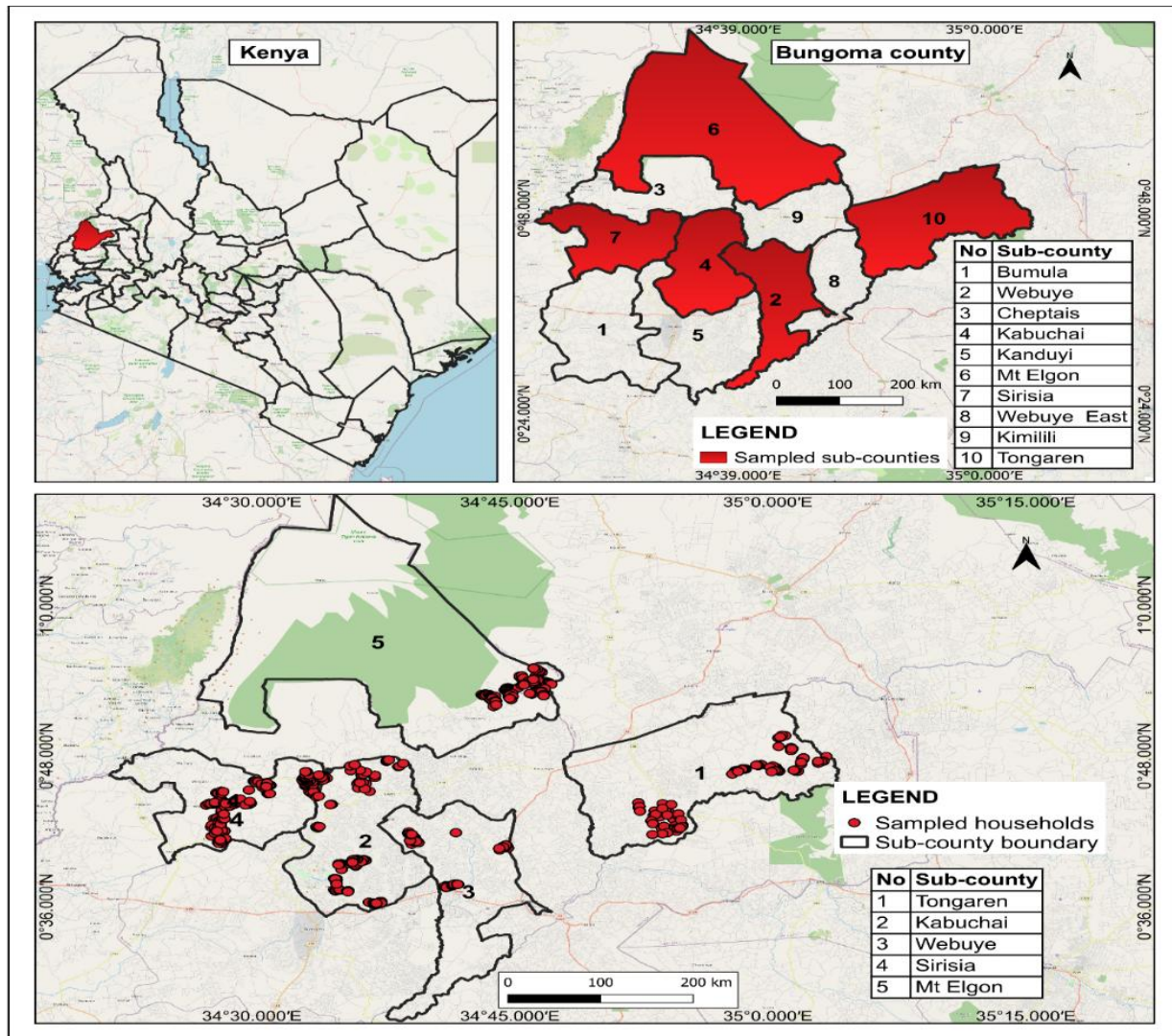
This study contributes to the growing body of literature on intensity of adoption by use of the FRM. It uses the FRM to examine socioeconomic factors influencing the intensity of adoption of improved maize varieties in Bungoma County. The study is in line with Vision 2030 and more recently, the Agricultural Sector Transformation and Growth Strategy 2019-2029 that strive to attain 100% food security for all Kenyans by 2030. High productivity translates to lowered consumer prices, whereas farmers adopting improved varieties realize higher income hence reduced poverty levels, reduced malnutrition, good environmental management and women empowerment. The low consumer prices due to increased maize supply leads to a reduced share required to purchase food hence increases consumer welfare. The factors determining the intensity of adoption from this study will act as a guide to researchers, producers and other stakeholders in the maize value chain in their quest to increase food security in Kenya.

## **Methodology**

### ***Study area***

Agriculture drives the economy of Bungoma county, and where almost all households plant improved maize varieties. The county is one of the leading producers of maize in the country, the fourth largest maize producer after Trans Nzoia, Uasin Gishu and Nakuru counties. Maize is both a food and cash crop for smallholder households in Bungoma County.

Figure 1 shows the map of Bungoma County. The selected sub-counties; Webuye, Kabuchai, Mt. Elgon, Sirisia and Tongaren were the main maize growing areas in the county. The annual rainfall in Bungoma County ranges from 400 -1800 mm, while the annual temperatures vary between 14.8<sup>0</sup>C and 27<sup>0</sup>C, and the main agro ecological zones are upper highlands (UH), lower highlands (LH), upper midlands (UM) and lower midlands (LM). The different agro-ecological zones give room for growing different maize varieties ranging from hybrid maize, OPVs and local varieties.



**Figure 1: Map of Bungoma County showing the study sites**

### ***Sample size and sampling***

The household survey used the national statistical sample frame developed by the Kenya National Bureau of Statistics (KNBS). A total of 500 households were selected, a sample size that was determined using the formula by (Israel, G. D., 1992).

$$N = N / (1 + N(e))$$

$$n = \frac{N}{1 + N(e)^2}$$

Where n is the sample size, N is the population size, e is the level of precision (taken as 10%)

The calculated minimum sample size in each selected sub-county was therefore 100, making a total of 500.

Pretesting of the questionnaire was conducted in Kanduyi sub-County. Farmers were selected using a systematic sampling approach, where a main land mark such as a road, church or school was the starting point of the transect that enumerators used to walk along, and select every 5<sup>th</sup> farmer for interview on the alternative side of the road or path. A structured questionnaire mounted on the open data kit (ODK) was administered to the 500 households by trained enumerators through face to face interviews. Data was collected in January-February 2022.

### ***Theoretical framework***

Two theories, the random utility theory (RUT) and expected utility theory (EUT) guide the discrete choice models used to model the process of decision making to adopt and utilize a technology. Both theories assume that given a set of alternatives, a farmer will always make a choice on the alternative that yields the maximum utility (Mercer, 2004). The EUT is used when the preferences are stated and the choices are made in the presence of uncertainties and there is an expected outcome (Polak & Liu, 2006). The farmers are assumed to weigh the expected benefits and costs from adoption of the technology against the benefits and costs from not adopting. The farmer adopts a technology if the expected utility from adoption decision ( $U_d$ ) is higher than that derived when one does not adopt ( $U_n$ ) (Kassie *et al.*, 2015). The RUT is applicable when preferences of the outcome are revealed and outcome decisions are made in an environment with no uncertainties. The utility is derived from the underlying characteristics or attributes of a given technology or good (Louviere *et al.*, 2000). Therefore, a good is described by its attributes that yield satisfaction to the small holder farmer if adopted. Adoption and use of a technology is taken as an outcome of optimization by heterogeneous farmers which takes place in the presence of availability of the technology, budget constraints and information asymmetry (Foster & Rosenzweig, 2010). The RUT was employed in the study to examine the determinants of the level (intensity) of adopting improved maize varieties.

The RUT considers adopter households as agents who make rational decisions to maximize utility in the presence of budget constraints, information asymmetry and technology availability (Gebre *et al.*, 2023). According to Baiyegunhi *et al.*, (2022), random utility suggests that a utility maximizing maize farmer will add a proportion of land under improved maize variety if the total benefits are greater than zero. According to Asiimwe *et al.*, (2022) the random utility function for a maize smallholder farmer facing a decision to increase a proportion of land under improved maize varieties was specified as;

$$P_{im} = \bar{P}_{im} + \varepsilon_{im} = X_{im}\theta + \varepsilon_{im}, i = 1, \dots, n$$

Where,  $P_{im}$  is the utility of alternative  $m$  for farmer  $i$ , and is a function of deterministic component  $\bar{P}_{im}$  and the random component  $\varepsilon_{im}$ ,  $X$  is the demographic characteristics (such as age, gender, land size, extension, credit access) and the technology specific

attributes (such as high yielding, early maturity, pest and diseases resistance and drought resistance) and a disturbance term assumed to be normally distributed with zero mean and constant variance, while  $\varepsilon_{im}$  is the stochastic element of the utility function which represent the unobserved attributes affecting farmer  $i$  choice on land allocation and measurement errors.

Therefore, a rational farmer would increase land under improved maize production if the expected utility driven from an additional proportion of land  $P_{i1}$  was higher than the one generated on normal land allocation  $P_{i0}$  in the presence of production constraints.

### ***Empirical framework***

To analyze the intensity of technology adoption, several empirical models have been used, which include Truncated regression, Tobit regression and censored, Poisson, Fractional response and Double hurdle models. The Truncated regression, Tobit regression and censored models are normally used to estimate continuous dependent variable that are restricted or bounded (Papke & Wooldridge, 1996, Misango et al., 2022). In this study, the dependent variable is an intensity of adoption which is defined as the total land under improved varieties divided by the total land allocated to production which is a fraction or proportion. Hence, Tobit, truncated and censored models will give biased estimates since they are constrained. Therefore, to account for this limitation the study used the Fractional Response Model (FRM) since FRM affirms more specific interpretations especially where observations at the end of the distribution are of importance for analysis. The FRM accounts for nonlinearity, and relaxes the numerous restricting assumptions that are necessary in traditional econometric models. The FRM extends the general linear models (GLM) to a class of functional forms that overcome the limitations of the outdated econometric models for variables that are bounded in nature (Wooldridge, 2015).

The study applied fractional logit model which assumes a logistic distribution of random disturbances and binds the estimated intensity of adoption of improved maize varieties between zero and one ((Papke & Wooldridge, 1996). The intensity of adoption was defined as the proportion of land under improved maize varieties per household divided by the total number of acres per household, which is bounded between zero and one. The general model of intensity of adoption is specified following the functional form for expected intensity of adoption of improved maize varieties  $Y_i$  of the  $i$ th farmer conditioned by  $X_i$  explanatory variables (Papke & Wooldridge, 1996) as;  $E(Y|X_i) = \mu(\beta X_i)$

Where  $Y_i$  represents the adoption intensity of improved maize varieties,  $X_i$  is a vector of farmer characteristics and technology-specific attributes and  $\beta$  a vector of unknown parameters to be estimated. The cumulative distribution function that follows a logistic distribution function is defined by  $\mu(\cdot)$  which represents a nonlinear link function satisfying  $0 \leq \mu(\cdot) \leq 1$  to ensure that the value approximated lie in the interval of 0 and 1 and  $E$  is the expectations operator.

The variables included in the model are specified in Table 1. The dependent variable was the intensity of adoption, which was specified as land under improved maize over total farming land the farmer had. The independent variables include household characteristics, institutional attributes and varietal attributes.

Table 1: Description of explanatory variables and used in the Fractional Response Model

<b>Variable Name</b>	<b>Variable description</b>	<b>Unit of Measurement</b>	<b>Expected signs</b>
<b>Dependent variables</b>			
<b>Adoption intensity</b>	Acres allocated to improved maize variety divided by total acres of farming land	Proportion	+
<b>Independent variables</b>			
<b>Household characteristics</b>			
Age	Age of household head in years	Years	+/-
Gender	Gender of the household head	1= male ,0= female	+/-
Farm experience	Number of years farmer farmed maize	Years	+
Household size	Number of persons in the household	Continuous	+
Off-farm income	Annual income outside the farm	Continuous	+
Group membership	Membership to a farmers group	(1= yes; 0 = otherwise)	+
<b>Institutional attributes</b>			
Extension service	Farmer contact with extension officer	(1=yes; 0 = otherwise)	+
Access to credit	Farmers access to any form of credit	(1 = yes; 0 = otherwise)	+
<b>Varietal attribute</b>			
High yielding	Variety is perceived to be high yielding	(1 = yes; 0 = otherwise)	+
Early Maturity	The variety is perceived to mature early	(1=yes; 0 =otherwise)	+
Pest and Disease tolerance	The variety is perceived to be resistance to pest and diseases	(1=yes; 0 =otherwise)	+

## Results and Discussion

### *Farmer characteristics, environment and preferences*

A consideration of farmer characteristics and farmer environment is important in order to explain/support the econometric results from the FRM model. This section looks at the household characteristics, farmer constraints and farmers' varietal preferences. Table 2 shows household characteristics of the surveyed households. The average land acreage in the Bungoma County study sites was 3 (2.89) with an average of 1.4 acres allocated to maize pure stand. According to the key informants, agricultural land in the county has been declining due to sub-division for inheritance. The average age of the household head was 51 years, meaning that the farming population in the study site was aging.

Table 2. Household characteristics in Bungoma County, Kenya

Variable	Bungoma (n=500)	
	Mean	Standard deviation
Household head age (years)	51.1	13.8
Household size (number of people)	7	3
Total land size (acres)	3.00	2.89
Total land under maize (acres)	1.7	1.9
Number of maize plots (number)	2	2
Size of main maize plot (acres)	1.4	1.6
Gender of household head	Frequency	Percent (%)
Female	111	28
Male	389	72
Level of education	Frequency	Percent (%)
Secondary	205	41.0
Primary	163	32.6

College/University	128	25.6
None	4	0.8

Source: survey data, 2022

Approximately 33.4% (n=500) produced maize for subsistence and did not sell any maize. The reasons for producing only for subsistence were: no surplus to sell (67%), objective for production was purely for consumption(28%) said their objective was to, while others said it was because of small land sizes (2%). The main constraints in maize production were high cost of inputs, pests and diseases and unpredictable weather as shown in Table 3.

Table 3: Maize production and marketing constraints in Bungoma County

Constraint	Frequency (n=500)	Percent
Production constraints		
High cost of inputs	144	28.8
Pests and diseases	142.5	28.5
Unpredictable weather	138.5	27.7
Post-harvest losses	37.5	7.5
Poor seed quality	21	4.2
Poor fertilizer quality	10.5	2.1
Others	6	1.1
Marketing constraints (n=500)		
Low prices	369	34.8
Low yields	161	15.2

Excess supply of maize	133	12.5
Post-harvest losses	103	9.7
Unpredictable weather	93	8.8
Long distance to markets	58	5.5
Other	144	13.6

A wide range of improved varieties was grown in Bungoma County but the main ones include H6213, H513, WH505, DK8031 and H516. The main reasons given for planting the stated varieties were high yielding of the varieties (30% of the respondents), good taste (17%), resistance to pests and disease (14%) and early maturing (14%). It is apparent that farmers were responding to climate change, hence preferred climate smart maize seed that is adapted to changing environmental conditions. Only 3% of the farmers said they planted the varieties because they fetched good prices.

#### *Fractional Logit Model results*

Table 4 presents the coefficients and marginal effects estimates from the results of the fractional logit model. The mean Variance Inflation Factor (VIF) score was 1.42, less than the critical value of 10, meaning that there was no multi-collinearity detected among the independent variables. The Breusch-pagan test fails to reject the null hypothesis of homoscedasticity ( $\text{Chi}^2(1) = 0.04$ ;  $\text{Prob} > \text{chi}^2 = 0.837$ ), thus indicating that there was no heteroscedasticity. The Wald statistic ( $\text{Wald chi}^2(11) = 72.59$ ) was significant at one percent level, meaning that the model has high predictive power. A total of five variables were identified as determinants for intensifying improved maize varieties in Bungoma County as shown in Table 4:

**Table 4: Determinants of intensity of adoption of improved maize varieties**

<b>Independent variables</b>	<b>Coefficient (robust std error)</b>	<b>Marginal effects (robust std error)</b>
Age	-0.011(0.0043) **	-0.0026(0.0011) **
Sex	-0.053(0.0910)	-0.013(0.0223)
Farming Experience	-0.004 (0.0049)	-0.001(0.0012)
Household size	-0.027(0.0151) *	-0.007(0.0037) *

Off-farm income	-0.121(0.0825)	-0.029(0.0202)
Extension service	-0.228(0.0898) **	-0.056(0.0219) **
Group membership	0.054(0.1006)	0.013(0.0246)
Access to credit	0.041(0.0888)	0.009(0.0217)
High yielding	0.117(0.0891)	0.029(0.0218)
Early yielding	0.294(0.0787) ***	0.0719(0.0191) ***
Tolerance to pests and diseases	0.134(0.0754) *	0.033(0.0184) *
Constant	0.689(0.2072) ***	
Number of Observations		498
Wald chi2(11)		58.78***
Breusch–Pagan/Cook–Weisberg Test for heteroscedasticity		Chi2(1) = 0.04 Prob > Chi2 = 0.8370
Pseudo R2		0.0149
log pseudolikelihood		-339.96322
Mean Variance Inflation factor		1.42

Source: Authors' own computation, 2023.

Note: *Values in parentheses are standard errors, 10 percent, 5 percent; and 1 percent significant levels are denoted by \*, \*\*, \*\*\* respectively*

The study findings show that a year's increase in the age of the household head reduced the probability of intensifying maize production by about 0.3%, meaning that older farmers put a smaller proportion of their land under improved maize production than the younger ones. This finding corroborates that of Mwaura et al., (2021), who found that older farmers had a negative influence on the intensity of adoption of organic based technologies. Similarly, Olawuyi & Mushunje, (2019) found a negative effect of older farmers on the intensity of use of soil and water conservation technologies in Nigeria. Uddin, (2020) reported a negative correlation between age and adoption of agricultural technologies in South Dakota. In addition, a study in Ghana by Addison et al., (2023) shows that age reduced the intensity of adoption of improved rice technologies. These findings confirm the age-old fact that risk aversion among farmers increases with their age. This can be explained by the fact that the ability to provide sufficient labor, good management and receive information reduces with age,

thus setting in risk aversion. It is easy to resonate with this result for the study area because improved maize varieties require more inputs, and in the face of unreliable rainfall due to climate change, risk aversion among farmers will increase, thus reducing the area under improved maize production, especially among older farmers. Bungoma County is a high rainfall area but it has increasingly received unreliable rainfall in the past years.

A larger household size reduced the intensity of adoption of improved maize varieties in the study area by about 1%, meaning more family members reduced the chance of putting more land under improved maize varieties. On the contrary, some studies have reported a positive correlation between household size and intensity of adoption. Mwaura et al., (2021) found a positive correlation between household size and the intensity of adoption of mulch and manure. A study by Addison et al., (2023) reports a positive correlation between the number of adults in a household and adoption of improved rice technologies. The total household size strongly influenced (positively) the intensity of adoption of improved maize varieties in Benin (Mahoussi et al., 2021). All these studies show that household size was a proxy for labor availability in the household, which may not always be the case in all studies. A household can be termed as either a production or consumption unit. A household with a higher proportion of family members who are not productive on the farm (the very young, sickly and old) can be termed as a consumption unit while those with a higher proportion of family members who are productive (young adults) can be termed as a production unit. Therefore, a labor-intensive technology in a household that is a consumption unit may have a negative effect on the intensity of adoption, while a labor-intensive technology in a household that is a productive unit may have a positive effect on the intensity of adoption. The effect of household size on the intensity of adoption may therefore depend on the composition of the household size and the nature of the technology. In this study, the households may have been a consumption unit, where a higher proportion of household members were not productive on the farm. The household size of 7 in the study area was higher than the national average household size of 4.

In this study, access to extension service reduced the probability of intensifying maize adoption by about 6%. This is contrary to the positive effect of extension to the intensity of adoption reported in some studies. For instance, Ngcinela et al., (2019) found a positive effect of extension to the intensity of adoption of genetically modified maize in the Eastern Cape Province of South Africa. Pedzisa et al., (2015) in their study deduced a positive influence of access to extension to intensity of adoption of conservation agriculture by smallholder farmers in Zimbabwe. Mahoussi et al., (2021) found that access to extension services had a significant and positive influence on the decision to intensify the use of improved maize seed Benin West-Africa. In their study conducted in Ghana, Kwawu et al., (2022) found access to extension service having a positive effect on the intensity of adoption of maize technological packages. Muluki et al., (2022) found that a household's access to extension services gave a positive impact on the intensity of adoption of irrigation technologies in Machakos County. Finally, Ume

et al., (2020) found access to extension to have a positive impact on intensity of adoption of odorless fufu technologies. However, the negative effect of extension on intensity of adoption (increase of proportion of land under maize) of improved maize varieties in the study area could be due to the fact that extension agents encouraged farmers to grow other crops that can increase food security in the face of climate change, and since the land size is fixed, the acreage under maize was reduced. Due to climate change, the national and county governments have encouraged smallholder farmers to diversify crop production to minimize crop failure. Most improved maize varieties require high rainfall and purchased inputs like inorganic fertilizer. Unreliable rainfall therefore makes farmers plant more drought and pest resistant crops like sweet potatoes, sorghum and cassava at the expense of improved maize varieties. Maize as a staple food in Kenya, and more so in Bungoma County is therefore threatened, and this may be a threat to food security if the production of climate smart crops does not increase significantly. The goal of every county in Kenya is to increase food security.

The study results show that the positive attributes anticipated from growing improved maize varieties by farmers increased the intensity of adoption. The anticipated early maturing and disease tolerant varieties attributes increased the probability of adoption by 7% and 3.3% respectively. This finding lends support to similar studies conducted in Africa. In their study on intensity of adoption of integrated pest management practices in Rwanda, Misango et al., (2022) found that perceived benefits of the push-pull technology had a positive impact on the intensity of adoption of the technology. A study in Ghana by Addison et al., (2023) shows that perceived intensive use of labour and capital significantly reduced the probability of adoption of rice technologies. The expectation of increased yield from improved maize seeds highly influenced the intensity of adoption of improved seed in a study conducted in Ethiopia by Mahoussi et al., (2021). A producer's perception of profitability strongly influenced the probability of adoption of precision agriculture technologies in South Dakota, in the United States (Kolady et al., (2021). According to Derwisch et al., (2016), increased maize variety adoption has been attributed to their high yield potential followed by early maturity and drought tolerance as key traits in Malawi. A study by Marenya et al., 2021 reports that farmers were willing to pay for novel traits such as drought tolerance, good ear aspect, high adaptation while forgoing on high yield performance. These studies are a pointer to the fact that the inherent technology characteristics as well as the complementary inputs are a strong determining factor in adoption intensity.

### **Conclusions and Recommendations**

This study sought to find out the factors influencing the intensification of improved maize varieties in Bungoma County, where primary data from 498 households out of the 500 households' samples was used for analysis. This paper contributes to the literature on intensification of agricultural technologies, specifically to intensification of improved maize varieties. In this study, the factors influencing adoption intensity of improved maize varieties can be categorized into personal characteristics of the farmer

(age, and household), institutional factor (extension service) and varietal factors(early maturing benefit).

To increase food security, the extension service in the counties needs to pay special attention to older smallholder farmers to address the causes for their risk aversion given that the results show that the farmers are on average aged (51 years). The extension service should also encourage the youth to get into agriculture because they are more likely to adopt improved technologies than old farmers. The perceived benefits of improved varieties came out as a strong determinant for intensity of adoption, thus demonstrating how the possibility of getting benefits from a technology can intensify its adoption. To intensify the use of new technologies research should start from the user of the technology to understand the farmers' desired attributes in a technology, and once the technology is developed farmers need to be sensitized on the positive attributes of the technology. These results underscore the need to have a strong research-extension linkage in the counties where researchers can demonstrate technology benefits to the end-users.

The results also demonstrate the strong influence that extension has on food security and in particular on the intensification of improved maize varieties in Bungoma County, where access to extension service may have encouraged the production of other crops at the expense of putting more land under improved maize varieties. Extension should encourage the production of climate smart maize alongside other climate smart food crops in order to increase food security.

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