African Journal of
Agricultural and Resource Economics
Volume 17, Number 3 (2022), pp 224–238

Impact of climate-smart maize varieties on household income among smallholder farmers in Kenya: The case of Embu County

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Received: August 2022
Accepted: December 2022

DOI: https://doi.org/10.53936/afjare.2022.17(3).15

Abstract

Variability in climate and debility in soil fertility affect agrarian production, especially in sub-Saharan Africa, and thus threaten food security. This has prompted the seed sector to introduce various varieties of climate-smart maize in Kenya and release them in the market. In contrast, there is little experiential insight into how the adoption of these varieties by small-scale farmers affects their household income. This paper used cross-sectional data to evaluate the implications of climate-smart maize varieties on small-scale farmers' household income in Embu County in Kenya. The endogenous switching regression model was used to estimate the influence of climate-smart maize adoption on household income. Based on survey data obtained from 550 maize farmers in Embu County, the results show that age, education, land under climate-smart maize varieties, and distance to the market positively influenced the income level of the adopters. The findings further reveal that the decision to adopt the climate-smart maize varieties had a significant positive effect of about 60% on farmers' household income. It therefore can be concluded from the results that the adopters would gain more from technology adoption. These results recommend policies that stimulate the adoption *of current climate-smart varieties, with an emphasis on adoption by youths, to create more jobs and increase household income to reduce poverty among smallholder farmers in Kenya.*

Key words: climate-smart maize varieties, adoption, endogenous switching regression, impact, Kenya

1. Introduction

Agricultural productivity is affected by climate variability and deterioration in soil fertility, which have threatened global food security over the years (Wheeler & Von Braun 2013). Due to climatic change, drought has become more severe and prolonged (Hyman *et al*. 2008). Smallholder farmers face severe food crises and sustained long-term poverty traps as drought increases due to their limited adaptive capacity (Bryan *et al*. 2013). In sub-Saharan Africa (SSA), one of the most prominent food crops is maize, which is adversely affected by drought. According to Fisher *et al*. (2015), around 40% of maize-growing areas in Africa face intermittent drought stress, resulting in a loss in yield of about 10% to 25%. Changes in climate lead to increased drought time, which gives rise to a drop in maize production by 22% in SSA (Schlenker & Lobell 2010). Daryanto *et al*. (2016) suggest that the manifestation of drought decreases maize yield by 39.2%, especially at the vegetative and productive stage, and this decreases farmers' income over time.

Policymakers, researchers and farming communities face challenges related to agriculture and climate, such as the mitigation of greenhouse gas emissions, flexibility to changes in the environment, and ensuring food security. To meet growing food demands and improving the livelihoods of poor smallholder producers, mitigation of and adaption to climate change and changes in the agriculture sector are of primary importance (AGRA 2014). Climate-smart agriculture (CSA) is one of the promising ways that have been identified to address the effects and causes of climate change. The development of climate-smart crop varieties, especially stress-tolerant maize varieties, has been achieved as an adaptive strategy to this situation. This has led to the introduction of drought-tolerant maize varieties for SSA, and the aim is to develop and deploy these varieties in zones where there are variations in rainfall patterns and climatic conditions (Wossen *et al*. 2017). Drought-tolerant maize varieties exhibit the ability to withstand drought and to produce higher yields compared to other commercial hybrids (Simtowe *et al*. 2019). According to Setimela *et al*. (2014), drought-tolerant maize germplasm produces about 40% more output under drought conditions than other commercial varieties.

In addition, ex ante economic analyses suggest that, if small-scale farmers would adopt drought-tolerant maize extensively, this would provide a change in welfare through improved production and reduced risk. It is estimated that the uptake of climate-smart maize varieties in SSA can produce a cumulative benefit of 362 to 590 million US dollars (USD) to both producers and consumers (Kostandini *et al*. 2009). Furthermore, according to Lunduka *et al*. (2017), a family cultivating stress-tolerant maize varieties can produce 247 kg per acre more than their counterparts who did not cultivate stress-tolerant varieties, generating an additional USD 240 per ha for the adopter families. Although ex ante analyses (such as those by Kostandini *et al*. 2009; La Rovere *et al*. 2014; Fisher *et al*. 2015; Holden & Fisher, 2015, Kassie *et al*. 2013) of the adoption of climate-smart varieties such as drought-tolerant maize varieties in SSA predicted a positive impact on both the yield potential and the returns to the household, ex post analyses require more work. Therefore, this study intends to fill this paucity in the literature on the effect of adopting these new, improved climate-smart maize varieties on smallholder farmers' income in Kenya by evaluating the impact of adopting climate-smart maize varieties on these households' income. The results from this study will play a key role in achieving the sustainable development goals relating to zero hunger, poverty reduction and climate change. Moreover, the adoption of climate-smart maize varieties will directly improve agricultural productivity and indirectly increase household income, which is in line with government programmes of attaining vision 2030. The rest of the paper is presented as follows: Section 2 discusses the methodology, while Section 3 presents the results and discussion. Finally, Section 4 presents the conclusion and policy recommendations.

2. Methodology

2.1 Theoretical framework

Smallholder farmers act as rational economic agents who aim to maximise their welfare, given a set of constrictions determined by market conditions, institutions, the biophysical environment, and the availability of information (De Janvry *et al*. 1991). The farmers are assumed to weigh the expected benefits and costs of the adoption of climate-smart maize varieties against the benefits and costs of not adopting. Therefore, following the expected utility theory (Mercer 2004), farmers decide whether or not to adopt technology, such as a climate-smart maize variety, given that the risk and uncertainty scenarios are assumed to be based on the assessment of expected utility (Schoemaker 1982). The farmer adopts a technology if the expected utility from the adoption decision (Uά) is higher than that derived when one does not adopt (Uη) (Kassie *et al*. 2015). In this study, the expected utility of the present value of agricultural returns and conditions of the adoption of yield-enhancing inputs such as climate-smart seed represent the farmer's preference.

Following Greene (2003), the expected utility for the household can be specified as a function of climate-smart seed (Z_{ik}), other technical factors and the socio-economic characteristics of the household (τ_i) (Equation (1)):

$$\pi_{ik} = \bar{\pi}(z_{ik}, \tau_i) + \varepsilon(z_{ik}, \tau_i) = x_{ik}\theta + \varepsilon_{ik}, k = 1,2; i = 1, \ldots, n, \tag{1}$$

where the deterministic factor of the utility function is $\bar{\pi}(z_{ik}, \tau_i)$, $\varepsilon(z_{ik}, \tau_i)$, also referred to as the stochastic element of the utility function. It represents the unobserved attributes affecting technology choice, heterogeneity in tastes and measurement errors:

$x_{ik}$is a matrix of covariates, z_{ik}, and τ_i; and θ is the vector of parameters.

Therefore a farmer plants the climate-smart maize seed if the expected returns from using it are higher than those generated by traditional seed varieties. The binary choice model of adoption of improved seed is thus specified in Equation (2):

$$y_i = I\{\pi_{i1} - \pi_{i0} > 0\} = I\{x_{i1}\theta + \varepsilon_{i1} - x_{i0}\theta + \varepsilon_{i0} > 0\} = I\{x_i\theta + u_i\}, \tag{2}$$

where $u_i = \varepsilon_{i1} - \varepsilon_{i0}$ is a random error term with zero mean, and θ is defined up to some scalar normalisation.

2.2 Study area

The study was carried out in Embu County, which is located in the eastern part of Kenya. Due to its proximity to Mt Kenya, the county's temperatures are likely to be an average of between 9°C and 28°C. The county receives considerable rainfall, with an average annual rainfall of 1 206 mm. The months from March to July are the wettest season, whereas the hottest season is experienced between January and mid-March. The main driver of the county's economy is agriculture, with more than 70% of the population working as smallholder farmers. Prominent cultivated food crops in the county are maize, beans, pigeon peas, with maize and beans grown as either intercrops or monocrops (Country Government of Embu 2013). The average farm size ranged between 2 ha and 2.8 ha per household in 2002 (Ouma *et al*. 2002).

2.3 Survey design and data collection

The study adopted a survey design in a natural research setting (Bartlett *et al*. 2001). Multi-stage sampling was used. In the first stage, Embu County was purposively selected due to the increased effect of climatic change in the area, changing patterns of agricultural production, and different agroecological zones, which give room for growing different varieties of maize. The second stage was a stratified sampling of adopters and non-adopters at sub-locations of Kyeni South Ward, because of the heterogeneity in its demographic distribution, which formed three agroecological zones. These agroecological zones created three strata, which were based on the topographical and ecological demarcation of the three zones. The sample size was determined using Krejcie and Morgan's (1970) formula of the finite population, which is written as:

$$s = (x^2 Np(1-p))/d^2\ (N-1)\ + x^2\ p(1-p), \tag{3}$$

where S = size of the sample, X = standard variation at a given level of confidence, p = sample proportion (assumed to be 0.5, since this would provide the maximum sample size), N = the size of the population, and d = acceptable error (the precision). Using Equation (3), with N = 27 438, d = 4%, X = 1.96 (as per the table of the area under the standard curve for the given confidence level of 95%), the preferred sample size was 587 farmers. This number was obtained as follows:

$$\frac{1.96^2 \times 27438 \times 0.5(1-0.5)}{0.04^2 \times (27438-1) + [1.96^2 \times 0.5(1-0.5)]} = 587.42 \text{ (which can be rounded off to be 587 farmers)} \tag{4}$$

This gave a sample size of 587. However, due to resource constraints concerning meeting all the respondents, only a total of 561 respondents were interviewed. After data collection, 11 questionnaires were discarded due to incomplete and poor responses. Therefore, the analysis was done for 550 respondents. The questionnaire was developed and the enumerators were trained to know the content of the questionnaire and the intent of the research. Pre-testing was done in Manyatta constituency with farmers who had similar characteristic as the targeted respondents. This was to ensure the clarity of the questionnaire. Data collection was done in 2019 using a semi-structured questionnaire administered face to face with the maize farmers in Embu County in Kenya.

2.4 Empirical framework

To understand the causal impact of the climate-smart maize variety on farmers' household income, information was needed on how much the adopters would have earned had they not decided to plant new varieties, and how much non-adopters would have earned had they decided to adopt (Ngoma 2018). Lack of information on the abovementioned gap brings about the problem of selection bias. According to Amare *et al*. (2012), it is not possible to estimate the impact of adopting technology based on non-experimental observations, since it is not possible to observe the outcome of adopters in the case they did not adopt. This bias is also a problem of missing data, since we cannot observe the same farmers if they had adopted and not adopted at the same time (Ngoma 2018). To address the issue of bias selection in a non-experimental scenario, different econometric approaches are used, such as instrumental variables regression and Heckman models (Ogundari & Bolarinwa 2018).

Heckman models include propensity score matching (henceforth PSM) and endogenous switching regression model (ESR). The PSM expects that outcome coefficient to be the same for the non-adopters and adopters, but recent empirical studies have proven this is not the case (Di Falco *et al*. 2011; Asfaw *et al*. 2012; Teklewold *et al*. 2013; Shiferaw *et al*. 2014). Further, PSM may cause biased estimations, which may lead to inconsistency and biased estimates, which may give misleading policy recommendations. Thus, the PSM method is less reliable due to unobservable characteristics of the farmers influencing self-selection into treatment. The current study therefore employed the ESR model, with the average treatment effect on the treated (ATT) being used to measure this impact. The ATT calculates the average variance in upshots of adopters when they have adopted the technology and when they have not (Khonje *et al*. 2015). The PSM is the most commonly used method to calculate ATT, but it ignores unobserved factors that influence the process of adoption. The ESR model has its own limitations, since it assumes that the adoption equation and the outcome equation error terms have a tri-variate standard distribution with a covariance matrix and a mean vector zero. Even though ESR has this shortcoming, it is the appropriate model to apply in the current study to make it possible to avoid selection bias and unobserved heterogeneity of the adopters and non-adopters (Wossen *et al*. 2017).

The study took two stage-treatment frameworks to model the impact of adopting a climate-smart maize variety on household income using the ESR approach. The first stage of the adoption decision on the climate-smart maize variety was modelled as a binary function using the probit model. The latent variable of a given household decision to use climate-smart maize varieties, CSA_i^*, is specified as:

$$CSA_i^* = \beta X_i + \mu_i \quad (5)$$

The Probit model was estimated on the observed outcome as follows:

$$\left.\begin{array}{l} CSA_i = 1 \text{ if } CSA_i^* > 0 \text{ and} \\ CSA_i = 0 \text{ if } CSA_i^* \leq 0 \end{array}\right\} \quad (6)$$

The ordinary least squares (OLS) regression model with selectivity correlation was applied in stage two to analyse the correlation between the outcome variable with established dependent variables subject to the adoption decision. The outcome regression equation function dependent on adoption was specified as an endogenous switching regime model, in the following manner:

$$\text{Regime 1: (adopters): } Y_{1i} = \beta_1 X_{1i} + \varepsilon_{1i} \text{ if } CSA = 1 \quad (7a)$$

$$\text{Regime 2: (non-adopters): } Y_{2i} = \beta_2 X_{2i} + \varepsilon_{2i} \text{ if } CSA = 0 \quad (7b)$$

In this study, the outcome variables (household income) were Y_1 for those who adopted and Y_2 for the non-adopters, where X_{1i} and X_{2i} were exogenous covariate vectors, β_1 and β_2 were parameter vectors, and ε_{1i} and ε_{2i} were the error terms of the outcome variable. According to Shiferaw *et al*. (2014), for the ESR to be identified in the adoption model, it is essential that the explanatory variables include a selection instrument to add on those instinctively produced by the non-linearity of the adoption selection model. These are the variables that affect the decision to adopt climate-smart maize varieties, but that do not directly affect the outcome indicators (Wossen *et al*. 2017). The selection instruments were chosen carefully by executing a simple falsification test, which was used to validate the instruments selected (Di Falco *et al*. 2011). The variable was a valid choice instrument, since it affected the climate-smart maize adoption decision, but did not affect the household income from the output variable directly. The error terms selected in Equation (5) and the outcomes of Equation (7) were presumed to have a tri-variate standard distribution, with a covariance matrix and mean vector zero written as:

$$cov(\mu, \varepsilon_1, \varepsilon_2) = \begin{pmatrix} \sigma_\mu^2 & \sigma_{\mu 1} & \sigma_{\mu 2} \\ \sigma_{2\mu} & \sigma_1^2 & . \\ \sigma_{2\mu} & . & \sigma_2^2 \end{pmatrix}, \tag{8}$$

where σ_μ^2 = var(μ), σ_1^2 = var($\mathcal{E}_1$), σ_2^2 = var($\mathcal{E}_2$), $\sigma_{\mu 1}$ = cov(μ, $\mathcal{E}_1$) and $\sigma_{\mu 2}$ = cov(μ,$\mathcal{E}_2$). σ_μ^2 is valued up to a scale factor and is assumed to be equal to 1, and $cov(\varepsilon_1, \varepsilon_2)$ is not defined, as y_1 and y_2 are not observed simultaneously (Maddalla 1983).

Depending on the selection condition, the values estimated for the error terms, $\mathcal{E}_1$ and $\mathcal{E}_2$, are non-zero; hence the prediction of β_1 and β_2 with OLS will give a biased estimate (Shiferaw *et al*. 2014). This means that the error term in selection Equation (5) is correlated with the error term in outcome Equation (7) (income function). Thus, subject to the sample selection, the predicted values of the error terms, $\mathcal{E}_1$ and $\mathcal{E}_2$, are not zero, which creates selection bias (Asfaw *et al*. 2012). The selectivity bias created was addressed through the use of ESR by predicting the inverse Mills ratios (λ_{1i} and λ_{2i}) and covariance terms ($\sigma_{\mu 1}$ and $\sigma_{\mu 2}$), and then including them as auxiliary regression in Equations (7a) and (7b). The bias is corrected as:

$$E\{\varepsilon_{i1}|CSA_i = 1\} = \sigma_{1i}\frac{\phi(\beta x_i)}{\theta[\beta x_i]} = \sigma_{1u}\lambda_{1i} \text{ and } E\{\varepsilon_{i1}|CSA_i = 0\} = -\sigma_{2i}\frac{\phi(\beta x_i)}{1-\theta(\beta x_i)} = \sigma_{2u}\lambda_{2i} \tag{9}$$

The absence of selection bias is rejected if $\sigma_{\mu 1}$ and $\sigma_{\mu 2}$ are significant. After obtaining the inverse Mills ratios, the ESR framework was applied to determine the average treatment effect of the untreated (ATU) and the treated (ATT) by matching the estimated values of the outcomes for the non-adopters and for those who adopted in the actual and counterfactual scenarios. In terms of Shiferaw *et al*. (2014) and Khoja *et al*. (2015), the study computed the ATT and ATU as follows:

Those who adopted CSMVs (observation of the sample):

$$E\{y_{i1}|CSA_i = 1; x\} = \beta_1 x_{1i} + \sigma_{1u}\lambda_{1i} \tag{10a}$$

Those who did not adopt CSMVs (observation of the sample):

$$E\{y_{i2}|CSA_i = 0; x\} = \beta_2 x_{2i} + \sigma_{2u}\lambda_{2i} \tag{10b}$$

Those who adopted had they decided not to adopt (counterfactual):

$$E\{y_{i2}|CSA_i = 1; x\} = \beta_2 x_{1i} + \sigma_{2u}\lambda_{1i} \tag{10c}$$

Those who did not adopt had they decided to adopt (counterfactual):

$$E\{y_{i1}|CSA_i = 0; x\} = \beta_1 x_{2i} + \sigma_{1u}\lambda_{2i} \tag{10d}$$

Therefore, ATT is defined as the expected change in an adopter's household income as the difference between Equation (10a) and (10c). The ATU, which is the expected change in the non-adopter's household income is the difference between Equation (10d) and (10b), as follows:

$$\text{ATT} = E\{y_{i1}|CSA_i = 1; x\} - E\{y_{i2}|CSA_i = 1; x\} \tag{11}$$

$$\text{ATU} = E\{y_{i1}|CSA_i = 0; x\} - E\{y_{i2}|CSA_i = 0; x\} \tag{12}$$

The error term was presumed to be normally dispersed in the context of ESR, while λ was the selection term that captured all probable effects of the dissimilarity in the unobserved variables.

Table 1 shows the exogenous covariates used in the model and their hypothesised signs.

Table 1: Description of expected sign of the explanatory variables

Variable name	Variable description	Unit of measurement	Sign
Dependent variables			
Household income	Annual total income	Continuous (Ksh*)	+
Independent variables			
Age	Age of household head in years	Years	+/-
Gender	Gender of the household head	1 = male, 0 = female	+/-
Education level	Number of years spent in school	Years	+
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	+
Extension service	Farmer contact with extension officer in the past year	(1 = yes; 0 = otherwise)	+
Group membership	Membership of a farmers group	(1 = yes; 0 = otherwise)	+
Credit access	Farmer's access to any form of credit	(1 = yes ; 0 = otherwise)	+
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)	+

* Ksh = Kenyan shilling

The dependent variable of the endogenous switching regression model used in the study was the effect of adoption of CSMVs on household income among smallholder maize farmers in Embu County, Kenya. It is laborious and complex to measure income directly. In this study, the measurement of household income comprised the total annual income from both farm and off-farm sources. The exogenous variables used in the model were informed by determinants of the expected utility theory and previous studies. These variables included the perceived benefit traits of adoption of the new technology, such as high yielding, early maturity and resistance to disease. Farmers' perceptions of these traits in relation to increasing productivity increased their likelihood of adopting the maize variety. Idrisa *et al*. (2012) found out that the trait of high yield in soya bean influenced farmers' decisions to adopt.

Farmers join groups to access advisory services and provide them with an unconventional learning ground (Rowley & Cooke 2014). In Rwanda, it was found that if farmers were members of a group, it increased their probability of adopting improved bean varieties (Larochelle *et al*. 2016). Contact with extension agents acts as a proxy for information delivery about new technology, hence farmers who had contact with an extension officer were expected to know more about the climate-smart maize varieties. Yirga *et al*. (2015) found in Ethiopia that access to extension services had a positive relationship with adoption behaviours. Age, education, household size and access to credit were used as control variables following previous studies (such as those of Teklewold *et al*. 2013; Timu *et al*. 2014; Yirga *et al*., 2015).

3. Results and discussion

3.1 Demographic and socio-economic characteristics

Understanding the farmers' social, economic and institutional attributes is useful for understanding smallholder farmers' decision-making processes. The results in Table 2 show that the average age of the maize producers in our study area was 58 years, with eight years of formal schooling. The maize producers have 26 years' experience in maize production, and an average of four household members. Most of the households (72%) were male-headed, with 62% of them being adopters. Among the interviewed farmers, 92.2% were older than 35 years, which is the age of a person considered to be a youth, showing the limited involvement of youth in agriculture. In terms of institutional factors, 77% of the farmers who adopted climate-smart maize varieties received extension services. However, the provision of extension services to farmers was still low, at 38%, implying that more extension services are required to enhance the greater adoption of new technologies. Similarly, only 26% of the farmers received credit, whereas 83% of the adopters sourced credit facilities. This percentage implies that farmers have low access to means of improving their financial capacity, hence they become constrained in terms of the extent and timely purchase of the required input to carry out maize production.

Table 2: Socio-economic characteristics of respondents by level of adoption

Continuous variables	**Pooled mean (std dev.)**	**Adopters' mean (n = 346)**	**Non-adopters' mean (n = 204)**	**t-test value**
Age of household head (years)	58.4 (14.19)	57.3 (14.52)	60.36 (16.10)	2.3825 **
Years of schooling	8.0 (3.69)	8.2 (3.53)	7.6 (3.92)	-0.9907
Number of years farmer farmed maize	26.9 (16.00)	25.9 (15.43)	28.43 (16.85)	1.7707 *
Household size	4.1 (1.82)	4.3 (1.80)	4.0 (1.80)	-1.5115
Distance to nearest input market in km	3.8 (0.30)	3.8 (0.44)	3.66 (0.30)	-0.2494
Log of off-farm income	7.2 (0.23)	7.6 (0.28)	6.6 (0.38)	-2.0800 **
Dummy variables		**Percentage of farmers**		**$\aleph^2$ value**
Gender of household head: Male	72	62.9	37.1	-3.1205***
Female	28	63	37	-4.9701 ***
Access to extension services (% yes)	37.5	76.7	23.3	-6.0273***
Farmers belonging to a group (% yes)	59.3	65	35	-5.1977***
Access to any form of credit (% yes)	25.8	83.1	16.9	-6.5780***

Note: ***, ** and * indicate statistical significance at the 1%, 5% and 10% level respectively
Source: Survey data (2019)

3.2 Results of endogenous switching regression model on the adoption impact of climate-smart maize varieties on household income

The determinants of adopting the climate-smart maize varieties were analysed first, after which the adoption effect of the climate-smart maize varieties on the household income of small-scale farmers was measured to understand the effect of the adoption on household income. The endogenous switching regression model was employed by using the full information maximum likelihood (FIML) method in estimating the selection equation (adoption) and the outcome equation (effect on household income of both adopters and non-adopters) jointly (Lokshin & Sajaia 2004).

The results in Table 3 present the endogenous switching regression (henceforth ESR) model. Columns 2 and 3 represent the results for the decision to adopt climate-smart maize varieties from the selection equation of the household income model, while columns 4, 5, 6 and 7 represent the outcome equations. Columns 4 and 5 represent the outcome equation for adopters, while columns 6 and 7 represent the outcome equation for the non-adopters. The study included a set of explanatory variables, such as the household characteristics and institutional factors, to analyse the correlation between the adoption decision and household income.

The results of the ESR model estimated using the FIML show that the estimated coefficient of correlation between the error terms of adoption of climate-smart maize varieties and the household income function, given by ρ^1, ρ^0, is significantly different from zero and negative. The results suggest that the decision to adopt and the effect of the adoption of climate-smart maize varieties are both influenced by observed and unobserved factors. The significance of ρ^1, ρ^0 indicates a self-selection bias in the decision to adopt the climate-smart maize varieties, hence the use of the ESR model for the correction of selectivity bias. The relationship between adoption and household income in the outcome equation implies that adopters' household income is relatively higher than that of non-adopters. Furthermore, the transformed correlation (r^1 and r^2) in the systems equations is negative and significant. The negative correlation implies that adopters are better off when they adopt climate-smart maize varieties in terms of household income than when they did not adopt. Moreover, non-adopters would have been better off if they had adopted climate-smart maize varieties compared to when they did not adopt.

Table 3: ESR results for adoption and the impact of adoption of climate-smart maize varieties on household income

Model specification	**FIML endogenous switching regression**					
	Selection equation		**Outcome equation**			
	Adoption (1/0)		Adopters = 1		Non-adopters = 0	
Variables	Coefficient	Robust std error	Coefficient	Robust std error	Coefficient	Robust std error
Socio-economic factors						
Gender	0.388	0.196	0.278 *	0.163	0.197	0.334
Age	-0.024 ***	0.006	0.013 **	0.006	0.026 **	0.015
Education level	-0.037	0.023	0.063 ***	0.020	0.112 *	0.063
Household size	-0.006	0.041	-0.035	0.035	-0.002	0.082
Land size	0.010	0.033	-	-	-	-
Land ownership	0.250 ***	0.068	-	-	-	-
Land under maize	-0.086	0.089	0.337 ***	0.061	0.399 ***	0.137
Distance to market	0.007	0.006	0.022 ***	0.003	0.045 **	0.019
Seed source	1.581 ***	0.187	-	-	-	-
Agronomic factors						
Fertiliser application	1.164 ***	0.173	-0.255	0.178	-0.769 **	0.338
Mode of tillage	0.304 **	0.178	0.418 ***	0.129	0.070	0.326
Mode of weeding	0.669 ***	0.261	-0.227	0.226	-0.766 **	0.319
Crop protection	1.842 ***	0.225	-0.261	0.269	-0.537	0.356
Institutional factors						
Credit access	0.727 ***	0.184	-0.269 **	0.139	0.361	0.293
Extension service	0.369 ***	0.182				
Group membership	0.206	0.158				
Perceived attributes						
High yielding	0.467 ***	0.174				
Early maturity	0.572 ***	0.170				
Pest and disease resistance	0.399 **	0.200				
Drought tolerance	0.464 ***	0.160				
Constant	-4.773 ***	0.734				
Model summary						
Number of observation		550	346		204	
Wald chi^2 (12)		131.69				
Prob > chi^2		0000				
Log pseudo likelihood		-1 123.05				
r^1			-0.474 ***	0.240		
r^2					-0.495 ***	0.168
Rho_1			-0.442 **	0.194		
Rho_2					-0.458 ***	0.133
Wald test of independent equations: $chi^2(1) = 12.91$ prob > $chi^2 = 0.0003$						

Note: * , ** and *** represent the significance at the 10%, 5% and 1% level respectively; r^1r^2: transformation of the correlation of the error terms in the adoption equation and outcome equation; $\rho1\rho0$: correlation coefficient between error terms of the system equation
Source: Survey data (2019)

Nevertheless, the results indicate the existence of heterogeneity in the sample of households because of the differences in the household income equation's coefficients between the adopted and nonadopted farming households. In addition, the likelihood ratio test for independence between the selection equation and the outcome equations was significant at 1%, indicating dependence between the two systems of equations.

The estimates in the selection equation in Table 2 suggest that the main drivers of farm households' adoption of climate-smart maize varieties (henceforth CSMV) ranged from socio-economic characteristics to varietal attributes. The respondent's age is significant at 1%, but negatively influenced farmers' decisions to adopt climate-smart maize varieties. Therefore, as the respondents' age increased, it reduced their likelihood of adopting CSMV. These results corroborate the findings of Kuntashula *et al*. (2014) and Ngoma *et al*. (2018), who observed a negative association between age and adoption of agricultural technologies.

Land ownership was statistically significant at 1% and positively influenced the adoption decision. This shows that, if a farming household owns land, it increases the household's likelihood of adopting CSMV. This result was consistent with that of Abdulai *et al*. (2011), who observed a positive relationship between land and the adoption of agricultural technologies. Source of seed positively and significantly influenced the decision to adopt, suggesting that those farmers who sourced their seeds from the agrovet were more likely to adopt climate-smart maize varieties. This would have been brought about by the fact that, when the farmer sources seeds from a certified agrovet, they are perceived to be original and not counterfeit, which in turns increases production and hence increases household income. The findings are consistent with those of Ghimire *et al*. (2015) in Nepal, who reported a positive relationship between availability of seeds and adoption of improved maize technologies.

The perception of agronomic factors such as fertiliser application, mode of tillage, crop protection and weeding were found to positively and significantly influence the likelihood of adoption of climate-smart maize varieties. This implies that, if a farmer managed the application of fertiliser and undertook other crop protection practices, such as pesticide application, it would increase the probability of adopting CSMV. In terms of mode of weeding and tillage, farming household that ploughed their land and did hand weeding were more likely to adopt climate-smart maize varieties. Access to extension services was positively and significantly related to the adoption of climate-smart varieties. This means that farmers who had contact with extension officers had a greater likelihood of adopting these maize varieties. This result is consistent with those of Di Falco and Veronesi (2011) and Maina *et al*. (2019), who found that access to extension officers increased the probability of a farmer adopting new agricultural technologies.

Credit access had a positive and significant effect on the adoption decision at the 1% level of significance, implying that farm households that had access to credit services were more likely to adopt climate-smart maize varieties. This result implies that it is essential for a farmer to access formal credit, since it acts as a source of financing the production of adopted maize varieties. These results are consistent with the findings of Abdulai and Huffman (2014) and Khanal *et al*. (2018), who noted an increase in the probability of adopting new agricultural technologies with the accessibility of credit. In terms of varietal attributes, namely high yielding, early maturity, drought resistance and resistance to pests and diseases, these were all positive and significant, implying that if a farmer perceived these varieties to have these traits, it would increase the likelihood of the farmer adopting them.

The results on the affect of adoption on household income are presented in columns 4, 5, 6 and 7 of Table 3 for the farmers who adopted and those who did not adopt. The ESR estimations of household income determinants of the farmers who adopted and those who did not adopt are presented in Table 3. At the same time, the prediction of the heterogeneity effects and treatment effects are shown in

Table 4. The findings (Table 3) indicate that the age of the respondents, their education level, land under climate-smart maize production and distance to the market had a positive and significant influence on increased household income for adopter and non-adopter farm households. Moreover, the gender of the household head, fertiliser application, mode of tillage, mode of weeding and access to credit appeared to have a differentiated impact on the household income of adopters and non-adopters. The gender of the respondent and mode of tillage in the outcome equation (column 4 of Table 3) had a positive and significant effect on household income in the adopters category. At the same time, there was a negative and significant effect of adopters' household income on the accessibility of credit. On the other hand, fertiliser application and mode of weeding in column 6 of Table 3 had a negative and significant impact on the household income of non-adopters.

The results in Table 4 present the main impact assessment and show the expected household income under the two conditions, namely actual and counterfactual. The predicted household income from the endogenous switching regression model was used to estimate the mean household income gap between the adopters when they adopted and had they not adopted, and the non-adopters and if they had adopted. Cells (a) and (b) represent the expected household income observed from the sample of adopters and non-adopters respectively. Cell (c) represents the expected household income of adopters if they did not adopt, while cell (d) represents the predicted household income of the non-adopters if they adopted.

Table 4: Impact of climate-smart maize adoption on household income in Embu County, Kenya

Sub-samples	Decision stages		Treatment effect
	To adopt	**Not to adopt**	
Log household income			
Farm households that adopted	(a) 10.861	(c) 9.138	(ATT) 1.7221(0.029)***
Farm households that did not adopt	(d) 11.439	(b) 10.319	(ATU) 1.1199(0.036)***
Heterogeneity effects (TH)	BH_1 = -0.578	BH_2 = -1.181	TH = 0.6022(0.046) ***

Note: *** represents significance at the 1% level
Source: Survey data (2019)

The expected log household income of the farming households that adopted was about 10.861, while it was about 10.319 for the farming household that did not adopt. The log difference in income indicated that the households that adopted the climate-smart maize varieties increased their household income by 0.54, which is approximated 54% more than that of the farming households that did not adopt. According to Di Falco *et al*. (2011), this is a simple comparison that may be inadequate for the researcher to conclude that, on average, the adopters of climate-smart maize varieties earned more than the farm households that did not adopt. Due to this inadequacy, the study used the heterogeneity effects to account for counterfactuals ((c) and (d)).

The last column of Table 4 shows the average treatment effects, which indicate the effect of the adoption on household income. The average treatment effect of the treated (ATT) is the difference between what adopters earned (a) and what adopters would have earned had they decided not to adopt (c). At the same time, the average treatment effect of the untreated (ATU) is the difference between what non-adopters would have made had they adopted (d), and what non-adopters earned without adoption (b).

The results in the last column of Table 4 show that ATT was positive and statistically significant, implying that the adoption of climate-smart maize varieties increased household income by 172%. The result suggests that adopters would lose an average log of 1.72 of the total household income if they had not adopted. On the other hand, the results from the ESR of the average treatment effect on the non-treated (ATU), which is positive and statistically significant, indicate that farmers who did not adopt would have increased their household income by 112% if they had decided to adopt climate-smart maize varieties. Therefore, the difference between the ATT and ATU gives us the heterogeneity effect (TH), which was 60.2%. These results imply that utilising climate-smart maize varieties increases the household income of adopters by 60%. These findings are consistent with those of Khonje *et al*. (2015), who concluded that the decision to adopt improved maize varieties increased adopters' crop income in Zambia. In their study in Zambia, Smale and Mason (2014) established that the decision to adopt hybrid maize varieties increased household income.

The last row of Table 4 shows a highly significant and positive transitional heterogeneity (TH) for the outcome variable, which suggests that the farmers who adopted and those who did not adopt were systematically different. Transitional heterogeneity measures whether the effect of using CSMVs is larger or smaller for farmers who adopted CSMVs had they not adopted, or for farmers who did not adopt CSMVs had they adopted (Ngoma 2018). The positive TH in this study implies that adopting CSMVs was more significant and beneficial for the farming household that had adopted compared to the non-adopters. These results agree with those of Asfaw and Shiferaw (2010). The significance of TH in the study implies that farmers who adopted would earn significantly more income than those who did not adopt in the counterfactual case (c). This significance of TH shows that there are some relevant sources of heterogeneity that make adopters better off and earn more than non-adopters, regardless of them adopting or not adopting climate-smart maize varieties. This finding corroborates the findings of studies by Di Falco *et al*. (2011), Khanal *et al*. (2018) and Quan *et al*. (2019), who observed a positive effect between agricultural technologies and household income.

4. Conclusion and policy recommendations

The adoption of climate-smart maize varieties offers farmers a higher output from maize production and an opportunity to increase returns and generate income, hence reducing the poverty level among smallholder farmers. The current study evaluated the effect of adopting climate-smart maize varieties on smallholder farmers' household income using an endogenous switching regression approach. The results show that there is great potential for increasing household income through the adoption of these varieties. The causal impact estimation from the switching regression suggests that the adopters have significantly higher household income than those who did not adopt, even after controlling for all confounding factors. In addition, the results show that those farmers who did not adopt would have gained from adopting climate-smart maize varieties if they had adopted. Therefore, stimulating agricultural growth, reducing poverty levels and improving food security depends largely on the decision to adopt climate-smart agricultural technologies such as climate-smart maize varieties. There thus is a need for greater adoption to enable more people to benefit from climate-smart maize varieties.

The finding of this study suggest that more efforts and resources need to be directed to agriculture to promote the adoption of climate-smart technologies. The agriculture sector has not been receiving a sufficient allocation of resources from the county government, making extension services almost non-existent. Therefore, there is a need to reinforce the extension services already in place to enhance access to information, which in turns will increase the adoption of climate-smart agricultural technologies.

Furthermore, the age of the maize farmer contributed to the adoption decision. Younger farmers are more likely to adopt new technologies compared to older farmers. Consequently, to increase income and reduce the unemployment rate among the youth, strategies that will make agribusiness more attractive to the youth are recommended. This can be done by formulating policies that favour youth and that are geared towards easier access to the production factors, such as land, which is mostly held by older farmers.

The positive influence of access to credit on adoption in the endogenous switching model and the negative impact on adopters' household income suggests that policies that enhance access to affordable credit could facilitate the adoption of new climate-smart agricultural technologies. This can be done by designing public policies that link with financial institutions and farmers' needs. Lending institutions such as commercial banks and micro-finance should work out policies that will make affordable credit available to farmers by lowering interest rates and simplifying the application process.

Acknowledgements

We acknowledge all the respondents for their time and for volunteering to be part of this study. We also take this chance to thank all the enumerators who assisted in data collection to provide us with conclusive data for this study. Finally, our special gratitude goes to Africa Economic Research Consortium (AERC) and the Kenya Agricultural and Livestock Research Organization (KALRO), for funding this study.

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