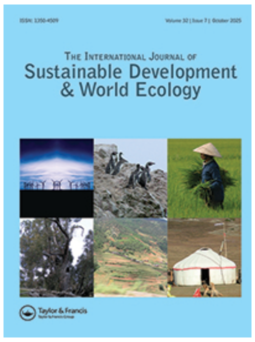

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Effect of adopting stress-tolerant maize varieties on yields and food security in Kenya

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ABSTRACT

Maize is the staple food for most households in Sub-Saharan Africa, and stress-tolerant maize varieties (STMV) are promoted to mitigate the impacts of climate change. However, the drivers and effects of STMV adoption on maize productivity and food security remain insufficiently understood. This study examines STMV adoption among 540 smallholder farmers in Kenya using Poisson and Probit models within an endogenous switching regression framework. Results indicate that adopters achieved 27.5% higher yields than non-adopters, with potential counterfactual gains of 69.2%. STMV adoption reduced vulnerability to food insecurity by 35.4% and increased the likelihood of food security by 22.3%, suggesting substantial benefits for non-adopters if they adopt the technology. Key drivers of adoption included male-headed households, frequent extension contact, and fertilizer use, while barriers involved high labor requirements, livestock ownership, larger farm size, soil fertility status, and distance to input markets. The findings underscore STMV's potential to enhance maize productivity and food security, contributing to the Sustainable Development Goals of 'No Poverty,' 'Zero Hunger,' and 'Climate Action.' Policy interventions should focus on overcoming adoption barriers, promoting technology bundles (e.g. seed and fertilizer), and implementing gender-inclusive strategies. Enhancing market access and scaling up adoption among non-adopters could maximize yield and food security gains, particularly in fertile and climate-vulnerable regions. These measures would ensure equitable benefits for marginalized farmers in Kenya and similar contexts, supporting resilient and sustainable maize production systems.

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Adoption drivers; climate change; endogenous switching regression; intensity of food insecurity; maize

1. Introduction

Maize is the primary staple food for most households in Sub-Saharan Africa (SSA); however, climate change increasingly threatens its production (Obunyali et al. 2024). Effects such as drought stress have adversely impacted yields, undermining the income, food security, and nutrition of millions of smallholder farmers in SSA (Fisher et al. 2015; Wossen et al. 2017; Worku et al. 2020; Gebre, Mawia, et al. 2021; Abate et al. 2023; Adéchian et al. 2023).

In Kenya, where maize plays a central role in agriculture and food security, yields remain low. This is largely due to abiotic stresses like poor soil fertility, heat, and frequent droughts alongside biotic challenges such as as pests (e.g. fall armyworm and stem borers) and diseases (e.g. maize lethal necrosis and gray leaf spot) (Cairns and Prasanna 2018; Worku et al. 2020; Radeny et al. 2022). Socioeconomic barriers, including limited access to farm inputs, weak agronomic support, poor market access, further constrain productivity (Simtowe et al. 2021; Wanjira et al. 2022). To address these challenges, Stress Tolerant Maize Varieties (STMV) have been developed and disseminated by the International Maize and Wheat Improvement Centre (CIMMYT), in collaboration with the Kenya Agricultural and Livestock Research Organization (KALRO) and private seed companies (Simtowe et al. 2021). These varieties offer improved tolerance to drought, heat, and low soil fertility, while also being resistant to key pests and diseases. STMV are expected to boost yields by 20–30%, reduce production risks, and improve the resilience of maize systems in eastern Africa (Simtowea et al. 2019; Simtowe et al. 2021); however, empirical studies on the impact of STMV adoption and associated drivers are scarce in this region particularly in Kenya.

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Evidence suggests that STMV adoption enhances household resilience to climate variability, improves food security, and increases both yields and farm income (Fisher et al. 2015; Wossen et al. 2017; Lunduka et al. 2019; Gebre, Mawia, et al. 2021; Kamara et al. 2024). However, adoption of STMV by smallholder farmers remains low (Adéchian et al. 2023), and the drivers of adoption are not fully understood (Simtowe et al. 2019, 2021; Simtowea et al. 2019; Gebre, Mawia, et al. 2021). The average STMV adoption rate in SSA is around 52% (Walker and Alwang 2015). While this rate seems modest, it needs to be analyzed based on different categories of farmers and the specific context of each SSA country (Simtowe et al. 2019). For instance, Adu et al. (2021) in Ghana reported low adoption of STMV and a low cultivar replacement rate. A similar observation was made by (Simtowe et al. 2019, 2021) in Uganda and Kenya, respectively. Voss et al. (2021) noted that the slow growth rate of STMV adoption discourages promoters from benefiting from their investment in breeding. Several reasons for low adoption and slow growth in adoption rates have been reported in the literature. A lack of information, farmer knowledge, and access to seeds are the main barriers to STMV adoption (Fisher et al. 2015; Simtowe et al. 2021). These constraints are reflected in high seed prices, which make access to technology particularly challenging for vulnerable groups (Fisher et al. 2015; Simtowe et al. 2021), resulting in gender disparities in STMV adoption (Gebre et al. 2019; Voss et al. 2021). Furthermore, farmers are reluctant to adopt new varieties when future access to technology is uncertain (Simtowe et al. 2019).

Despite the growing body of literature on STMV, critical research gaps remain, particularly in Kenya. While many studies have examined the impacts of STMV on yields and food security, they often fail to adequately account for methodological challenges such as selection bias and unobserved heterogeneity. These arise because farmers self-select into adoption, and adopters may differ systematically from non-adopters in both observable and unobservable ways, biasing impact estimates if not properly addressed (Maddala 1983; Lokshin and Sajaia 2004). To overcome these issues, this study employs an Endogenous Switching Regression (ESR) framework combined with Probit and Poisson models using Instrumental Variables (IV). The ESR model corrects for endogeneity by jointly estimating the adoption and outcome equations within a counterfactual framework, while IV techniques help to address the potential endogeneity of explanatory variables (Lokshin and Sajaia 2004; Di Falco et al. 2011). This methodological approach offers a more credible estimation strategy than standard regression or matching techniques, especially for impact evaluation under non-random treatment assignment.

Furthermore, most existing studies measure food security using categorical or binary indicators, without capturing the intensity of food insecurity experiences. This study addresses this gap by incorporating count-based and probabilistic measures of food insecurity that better reflect the depth and severity of the problem. In addition, the heterogeneity in both adoption and impact between different types of smallholder farmers remains underexplored. Addressing these issues with robust econometric tools and more granular food security indicators will provide a richer and more reliable understanding of the effects of STMV adoption on productivity and household welfare in Kenya and beyond.

Using primary data collected through the Stress Tolerant Maize for Africa project, this study examines the adoption and impacts of STMV on maize yields and food security in Kenya. It contributes to the literature by (a) addressing the empirical evidence gap on STMV adoption in Kenya, and (b) providing insights into how the adoption of STMV could impact maize yield and household food security of smallholder farmers. Given the pivotal role of high-yielding maize varieties in food systems, understanding their impact is essential for designing effective agricultural interventions. This study also provides policy-relevant insights into adoption bottlenecks and strategies to enhance the uptake and sustained use of agricultural technologies.

Based on the introduction above, we furthermore outline the methodological framework in Section 2. The study area, survey design, and data are discussed in Section 3. Section 4 presents the empirical results and discussion, while Section 5 offers the conclusion.

2. Methodological framework

2.1. Conceptual framework

The random utility framework is used to model a farmer's decision to adopt or not adopt a STMV, as established in previous studies (Abdulai and Huffman 2014; Jaleta et al. 2018; Dontsop Nguezet et al. 2020; Kamara et al. 2024). The framework assumes that a rational farmer seeking to maximize utility will adopt an STMV if the expected utility (economic benefits such as yield and food security) associated with adoption, U_{1i}, is greater than the expected utility associated with non-adoption, U_{0i}. In other words, adoption occurs if the expected utility difference, $E\left(U_i^*\right) = U_{1i} - U_{0i}$, is positive, that is, $E\left(U_i^*\right) > 0$. However, this latent utility difference between adoption and non-adoption of STMV is not directly observable.

2.2. Analytical framework

Since the net expected utility is unobservable, a farmer's decision to adopt or not adopt an STMV can be expressed as a function of observable characteristics (Z_i) and an error term (η_i) within the following latent variable framework, estimated using a binary probit regression model:

$$M_i^* = Z_{i\beta} + \eta_i$$

$$where\ M_i = \begin{cases} 1\ if\ Z_{i\beta} + \eta_i > 0 \\ 0\ otherwise \end{cases} \quad (1)$$

where M_i is a binary indicator variable that takes a value of 1 if a farmer is adopter[1] of STMV and 0 otherwise; Z_i is a vector of farmer, household, plot, village, and institutional level characteristics that influence the adoption decision; β is a vector of parameters to be estimated; and η_i is a random error term.

The primary goal here is to estimate the impact of STMV adoption on the yield and food security of maize-growing households. However, estimating and evaluating this impact using non-experimental data may be challenged by selection bias (Jaleta et al. 2018). Farmers may self-select into adoption, or the technologies may be targeted toward specific groups of farmers (Alene and Manyong 2007). Estimating the impact of STMV adoption on maize yield and food security without accounting for these selecting issues might suffer from potential endogeneity bias.

To reduce selection bias and endogeneity problems, many impact assessment studies have employed the endogenous switching regression (ESR) model (e.g. Alene and Manyong 2007; Di Falco et al. 2011; Shiferaw et al. 2014; Jaleta et al. 2018; Melesse et al. 2023). Accordingly, this study applies the ESR model to correct for potential selection bias and endogeneity. The ESR framework captures the treatment effect of adoption by allowing the treatment variable to interact fully with both observable and unobservable factors that influence the outcome variables (Jaleta et al. 2018).

The ESR model simultaneously estimates separate outcome equations for adopters and non-adopters, along with the selection equation, using the full information maximum likelihood (FIML) estimator (Lokshin and Sajaia 2004, 2011). While it assumes normality, like the instrumental variables (IV) approach, the ESR model is more efficient than IV techniques (Maddala 1983). Moreover, the ESR model has the advantage of simultaneously controlling for factors affecting treatment and disentangling factors influencing outcomes (Melesse et al. 2023). It also accounts for structural differences between adopters and non-adopters in their respective outcome functions (Alene and Manyong 2007).

The estimation of the ESR model proceeds in two stages. In the first stage, a probit adoption model is estimated, while the second stage estimates separate outcome equations for each outcome variable, correcting for the selection problem. As defined in the selection equation (Eq. 1), M_i is a binary variable derived from the utility-maximization framework and represents the observed adoption status of a maize farmer, where $M_i = 1$ if the farmer reported planting STMV on a plot, and $M_i = 0$ otherwise.

Conditional on the adoption decision, the outcome equations can be represented by switching regimes as follows:

Regime 1 (adopters):

$$Y_{1i} = \beta_1 X_{1i} + \varepsilon_{1i} \quad if\ M_i = 1 \quad (2a)$$

Regime 2 (non-adopters):

$$Y_{2i} = \beta_2 X_{2i} + \varepsilon_{2i} \quad if\ M_i = 0 \quad (2b)$$

where Y_{1i} and Y_{2i} are outcome variables for adopters (Regime 1) and non-adopters (Regime 2), respectively; X_{1i} and X_{2i} are vectors of exogenous covariates; β_1 and β_2 are vectors of parameters to be estimated; and ε_{1i} and ε_{2i} are error terms associated with the outcome variables. The error terms in the selection and outcome equations (Eq.1, 2a, and 2b) are assumed to follow a trivariate normal distribution with zero mean and a covariance matrix specified as:

$$cov(\eta, \varepsilon_{1,}\varepsilon_2) = \begin{bmatrix} \sigma_\eta^2 & \sigma_{\eta 1} & \sigma_{\eta 2} \\ \sigma_{1\eta} & \sigma_1^2 & 0 \\ \sigma_{2\eta} & 0 & \sigma_2^2 \end{bmatrix}$$

where σ_η^2 is the variance of the selection equation error term η; σ_1^2 and σ_2^2 are the variances of the outcome equation error terms ε_1 and ε_2, respectively; $\sigma_{\eta 1}$ and $\sigma_{\eta 2}$ represent the covariances between the selection error η and the outcome errors ε_1 and ε_2, respectively. All other covariances (e.g. between ε_1 and ε_2) are assumed to be zero, reflecting independence of the outcome disturbances across regimes (Maddala 1983).

The expected values of ε_1 and ε_2 conditional on sample selection are non-zero, as the error term in the selection equation (Eq. 1) is correlated with the error terms of the outcome equations (Eq. 2a and 2b):

$$E[\varepsilon_{1i}|M_i = 1] = \sigma_{1\eta}\frac{(\phi(Z_{ia}))}{(\Phi(Z_{ia}))} = \sigma_{1\eta}\lambda_{1i}$$

$$E[\varepsilon_{2i}|M_i = 0] = \sigma_{2\eta}\frac{(\phi(Z_{ia}))}{(1 - \Phi(Z_{ia}))} = \sigma_{2\eta}\lambda_{2i}$$

where $\phi(\cdot)$ and $\Phi(\cdot)$ are the standard normal probability density and cumulative distribution functions, respectively. λ_{1i} and λ_{2i} are the inverse Mills ratios, computed from the selection equation (Eq. 1) as

$$\lambda_{1i} = \frac{(\phi(Z_{ia}))}{(\Phi(Z_{ia}))}, \lambda_{2i} = \frac{(\phi(Z_{ia}))}{(1 - \Phi(Z_{ia}))}$$

and included in outcome equations (Eq. 2a and 2b) to correct for selection bias in a two-step estimation procedure. Thus, the selection-corrected outcome equations become:

Regime 1 (adopter):

$$Y_{1i} = \beta_1 X_{1i} + \sigma_{1\eta}\lambda_{1i} + \delta_{1i} \quad \text{if } M_i = 1 \tag{3a}$$

Regime 2 (non-adopter):

$$Y_{2i} = \beta_2 X_{2i} + \sigma_{2\eta}\lambda_{2i} + \delta_{2i} \quad \text{if } M_i = 0 \tag{3b}$$

where δ_{1i} and δ_{2i} are error terms with conditional zero means. The FIML method was applied to obtain consistent estimates (Lokshin and Sajaia 2004, 2011). Different model specifications were estimated depending on the distribution of the outcome variable. Importantly, the ESR framework can be applied to continuous, binary, censored, or count outcomes, as it involves estimating the selection and outcome equations simultaneously (Melesse et al. 2023). In this study, we consider three outcome variables.

The first outcome variable is household maize yield, which is continuous. Accordingly, the ESR model is estimated in Stata using the *movestay* package (Lokshin and Sajaia 2011). The second outcome is the Household Food Insecurity Access Scale (HFIAS) score, which is a non-negative count variable ranging from 0 to 27. To estimate the impact of STMV adoption on household food insecurity, we employ an endogenous switching Poisson model. Treatment effects are estimated using the *teescount* command following *escount* in Stata version 17 (Hasebe 2020). The third outcome, 'food secure,' is a binary variable. For this outcome, we apply an endogenous switching probit model, estimated in Stata using the *switch_probit* package (Lokshin and Sajaia 2011).

Although the nonlinearity in the selection equation allows for the simultaneous identification of the adoption and outcome equations, it is generally recommended to include exclusion restrictions based on valid instrumental variables in the adoption equation. This approach ensures more robust identification (Shiferaw et al. 2014; Christophe et al. 2020; Melesse et al. 2023). Previous studies have employed instruments related to access to information on improved varieties, such as access to extension services, membership in farmers' cooperatives, and distance to input markets (Shiferaw et al. 2014; Tesfaye and Tirivayi 2018; Christophe et al. 2020; Melesse et al. 2023). Farmers adopt improved varieties only if they have information or knowledge about them (Melesse et al. 2023). Following this reasoning, we use the frequency of contact with extension agents and distance to input markets as instruments for STMV adoption. These variables are expected to be correlated with the adoption decision but are unlikely to directly affect the outcome variables or correlate with the unobserved error terms in Equations (2a) and (2b).

The validity of an instrumental variable (IV) strategy depends on two key conditions: the relevance and exclusion restriction criteria (Melesse and Cecchi 2017; Melesse et al. 2023). While instrument relevance is relatively straightforward to establish, satisfying and convincingly demonstrating the exclusion restriction is often more challenging. A falsification test can be employed to assess the validity of the instruments (Di Falco et al. 2011). The principle underlying this test is that the instruments should not influence the outcome variables among non-adopter households. Hence, the instruments are considered valid if they significantly predict the adoption of STMV but do not have a significant effect on the outcomes of non-adopter households.

This study employs two instrumental variables, distance to the input market and the number of extension contacts, to identify the causal effects of STMV adoption on maize yield and household food security, respectively. The relevance of distance to the input market stems from its strong correlation with farmers' adoption of STMV. Farmers located farther from input markets face higher transaction costs, such as longer travel times and increased transportation expenses, which reduce their likelihood of accessing and adopting STMV seed. Thus, distance to the input market influences STMV adoption but does not directly affect maize yield except through its impact on adoption. Since geographical isolation alone is unlikely to influence yield without affecting access to inputs or technologies, the instrument satisfies the exclusion restriction. Furthermore, the falsification test confirms no direct association between distance to input markets and maize yield, supporting the exogeneity of this instrument (Appendix Table A1).

Similarly, the number of extension contacts serves as a valid instrument for food security. Its relevance arises from its strong association with participation in STMV interventions, as extension services provide critical information, training, and technical support that promote the adoption of improved varieties. Therefore, extension contacts are expected to influence food security only indirectly through STMV adoption. For instance, the frequency of contact with extension agents, without corresponding changes in production practices, is unlikely to affect food security outcomes directly. The falsification test also supports the validity of this instrument by showing no direct association between extension contacts and household food security (Appendix Table A1).

By satisfying both relevance and exclusion restrictions, the two instruments meet the exogeneity condition, eliminating concerns about unobserved confounders. Consequently, the estimated effects of STMV adoption on maize yield and household food security reflect the true causal impact of adoption rather than bias arising from endogeneity or omitted variables.

2.2.1. Treatment effects

Once the various models are estimated, the next step is to compute the average treatment effect on the treated (ATT) and on the untreated (ATU) by deriving the expected values of the outcome variables for adopters and non-adopters under both actual and counterfactual conditions. These expected outcomes are presented in Table 1 and defined as follows:

Actual (observed) outcomes:

$$E[Y_{1i}|M_i = 1] = \beta_1 X_{1i} + \sigma_{1\eta}\lambda_{1i} \quad \text{(adopter with adoption)} \tag{4a}$$

$$E[Y_{2i}|M_i = 0] = \beta_2 X_{2i} + \sigma_{2\eta}\lambda_{2i} \quad \text{(non − adopters without adoption)} \tag{4b}$$

Counterfactual outcome:

$$E[Y_{2i}|M_i = 1] = \beta_2 X_{1i} + \sigma_{2\eta}\lambda_{1i} \quad \text{(adopters had they not adopted)} \tag{4c}$$

$$E[Y_{1i}|M_i = 0] = \beta_1 X_{2i} + \sigma_{1\eta}\lambda_{2i} \quad \text{(non − adopters had they adopted)} \tag{4d}$$

It is possible that households adopting STMV achieve better outcomes (e.g. higher maize yield and greater food security) than non-adopting households, even in the absence of adoption, due to unobserved characteristics that predispose them to perform better. The conditional expectation equations can be used to estimate this base heterogeneity (BH) effect, which captures the influence of such unobserved characteristics (Di Falco et al. 2011). Another key parameter is transitional heterogeneity (TH), which assesses whether the impact of STMV adoption differs between adopters and non-adopters in the counterfactual scenario that they had adopted (Di Falco et al. 2011). It is calculated as the difference between ATT and ATU, that is:

$$TH = ATT - ATU$$

Alternatively, transitional heterogeneity can be computed as the difference between the base heterogeneity of adopters and non-adopters, expressed as:

$$TH = BH_1 - BH_2$$

Like the ESR models for continuous outcome variables, the switching Poisson and Probit models allow for the estimation of ATT and ATU for their respective outcomes (Lokshin and Sajaia 2011; Hasebe 2020). In addition, these models estimate the average treatment effect (ATE), which measures the expected impact of STMV adoption for households randomly selected from the population with similar observable characteristics.

Similar to the ESR model for continuous outcomes, treatment effects in the switching Poisson and Probit models may vary due to unobserved characteristics (Lokshin and Glinskaya 2009). However, unlike linear ESR models, the estimation procedure for switching Poisson and Probit models does not directly generate heterogeneity effects. To account for unobserved heterogeneity, we estimate marginal treatment effects (MTE), which capture the effect of STMV adoption on outcome variables for households whose adoption decisions are most responsive to the presence of the technology (Lokshin and Glinskaya 2009).

2.3. Food security measures

Based on previous studies, we hypothesized that adopting improved maize varieties such as STMV would significantly enhance farm households' food security. To measure household food security, we employed the Household Food Insecurity Access Scale (HFIAS) indicators to construct the food security index and define the cut-off point. HFIAS is an experiential measure of food insecurity that captures households' perceptions and experiences related to food access, reflecting both inter- and intra-household food distribution dynamics (Melesse et al. 2023). It records household behaviors associated with anxiety, uncertainty, and insufficient food access over the preceding 4 weeks (Coates et al. 2007; Headey and Ecker 2012).

Using the HFIAS approach, respondents were asked nine standardized questions regarding food insecurity experiences and the frequency of their occurrence within the past 30 days. The 'occurrence' questions identify whether a particular food insecurity condition was experienced, while the 'frequency-of-occurrence' questions determine how often it occurred (Appendix Table A2). If a respondent answered 'yes' to an occurrence question, a follow-up question captured whether the event occurred rarely (once or twice),

Table 1. Conditional expectations, treatment effects, and heterogeneous.

	Decision stage		
Subsamples	To adopt	Not to adopt	Treatment effects
Adopters	$(4a) = E(Y_{1i}\|M_i = 1)$	$(4c) = E(Y_{2i}\|M_i = 1)$	$(4a) - (4c) = ATT$
Non-adopters	$(4d) = E(Y_{1i}\|M_i = 0)$	$(4b) = E(Y_{2i}\|M_i = 0)$	$(4d) - (4b) = ATU$
Heterogenous effects	$(4a) - (4d) = BH_1$	$(4c) - (4b) = BH_2$	$ATT - ATU = TH$

Notes: (4a) and (4b) represent the conditional expectations of outcomes for adopters and non-adopters under observed condition, respectively, while (4c) and (4d) represent the conditional expectations of outcomes for adopters and non-adopters under counterfactual condition respectively. BH_i represents the effect of base heterogeneity while TH is the effect of transitional heterogeneity.

sometimes (3–10 times), or often (more than 10 times) during the previous 4 weeks (Coates et al. 2007).

The HFIAS score for each household was calculated by summing the frequency-of-occurrence values for all nine questions, resulting in a score ranging from 0 to 27, where a higher score indicates greater vulnerability to food insecurity. However, a concern with using HFIAS is that it assumes linear differences between scores and treats ordinal categories as interval-level data. In practice, this may not hold, as the intensity of food insecurity may not increase proportionally with the score. To address this issue, we constructed a binary variable (Food secure), which takes the value of 1 if the household experienced none of the food insecurity conditions and 0 if the household experienced at least one.

3. Study area, survey design, and data

3.1. Study area and survey design

The study is based on household survey data collected between November 2018 and January 2019. It involved a total sample of 540 farmers from six counties in Kenya: Makueni, Machakos, Embu, Tharaka Nithi, Kakamega, and Busia. These counties adequately represent the maize production potential and climate patterns of Kenya, particularly in regions where rural residents frequently experience climate hazards and shocks namely the western, central, and southern parts of the country.

The sampling method used to select farmers in this study involved a multistage random sampling technique. In the first stage, counties were selected within the Feed the Future zones of influence, focusing on areas where major crops such as maize are grown. This led to the selection of the six counties. In the second stage, three major crop-farming villages were selected in each county. Finally, at least 30 farmers were randomly selected from each of the three villages, resulting in 90 farmers per county and a total sample of 540 farmers.

A semi-structured questionnaire was designed and tested to collect a range of information related to the farmers' demographics, socioeconomic and agronomic characteristics, and food security conditions, including their perceptions of food security status. The questionnaire also captured information on social networks and institutional arrangements. Survey participation was voluntary, and informed consent was obtained from all interviewees.

3.2. Data and variables description

Table 2 presents the summary statistics of the main variables of interest. Approximately half (49%) of the sampled households were adopters of STMV. This finding aligns closely with Walker and Alwang (2015), who reported a 52% adoption rate of STMV across SSA. However, the current adoption rate is notably higher than that reported by Simtowe et al. (2021), who found a 26% adoption rate of STMV in Kenya. According to Simtowe et al. (2021), this lower adoption rate could potentially double to 52% as farmers' knowledge constraints are reduced, rise to 56% if seed access constraints are eased, and increase further to 60% if seed affordability barriers are addressed. The average maize yield among the sampled households was 5.626

Table 2. Presents descriptions of the sample (variables) by adoption status.

Variables	Description	Pooled ($n = 540$)	Adopters ($n = 267$)	Non-adopters ($n = 273$)	Difference
Outcome Variables					
Yield	Quantity of maize harvested quintal/ha	5.626	5.765	5.490	0.275***
HFIAS score	Household food insecurity (access) scale score ranging from 0 to 27, indicating least vulnerable to most vulnerable to food insecurity conditions	3.23	2.985	3.465	−0.480*
Food secure	Dummy, 1 if household is food secure and 0 otherwise	0.444	0.450	0.440	0.010
Independent Variables					
Gender (male)	Dummy, 1 if household head is male and 0 otherwise	0.701	0.737	0.666	0.071*
Age	Age of the household head in years	53.238	53.000	53.472	−0.472
Farm experience	Farming experience of the household head in years	24.437	23.816	25.044	−1.228
Head education	Education level of the household head in years	7.544	7.460	7.626	−0.166
Household size	Number of family members in the household	5.090	5.179	5.003	0.176
Labor days	Number of labor days worked on maize plots in AE	2.772	2.674	2.873	−0.198**
Livestock	Number of livestock owned by household in Tropical Livestock Unit (TLU)	1.948	1.873	2.022	−0.149
Nearest market	Distance to the nearest market center in km	3.446	3.115	3.769	−0.654**
Total farm	Total farm size owned by the household in hectares	2.468	1.968	2.957	−0.989***
Maize plot size	Size of the household maize plot	0.940	0.839	1.039	−0.200***
Maize harvested	Quantity of maize harvested in quintal	4.845	5.137	4.546	0.591*
Maize grain sold	Quantity of maize sold in the market in quintal	3.082	3.119	3.043	0.076
Soil fertility	Dummy, 1 if soil fertility is good and 0 otherwise	0.407	0.359	0.454	−0.095**
Extension	Number of contacts with extension agents per month	0.633	0.988	0.285	0.703***
Intercropping	Dummy, 1 if household use intercropping and 0 otherwise	0.709	0.692	0.725	−0.033
Organic fertilizer	Quantity of organic fertilizer applied per kg/ha	89.769	87.719	91.773	−4.054
Chemical fertilizer	Quantity of chemical fertilizer applied kg/ha	27.550	33.653	21.310	12.343***

Note: The results are significant at ***1%, **5%, and *10% levels, respectively.

quintals per hectare (q/ha), with adopters achieving slightly higher yields (5.765) than non-adopters (5.490). In terms of food security, the average HFIAS score was 3.23, with STMV adopters reporting lower levels of food insecurity. Similarly, 44% of the households were classified as food secure; although the difference was not statistically significant, adopters were somewhat more likely to be food secure than non-adopters.

While these descriptive comparisons are suggestive, they should be interpreted cautiously, as adopters and non-adopters may systematically differ in both observed and unobserved characteristics. Therefore, to account for potential selection bias and endogeneity, the subsequent sections employ econometric models that control for these differences and estimate the true causal effects of STMV adoption on maize yield and household food security.

The majority of sampled households (70%) were male headed, with a higher proportion observed among adopters. In East Africa, including the present study area, households are typically headed by a senior family member, most often the husband, wife, or an adult son, who assumes responsibility for household farming and food management activities. Consistent with this pattern, the survey revealed that in more than 90% cases, the household head was also the primary farmer. This indicates that, in this study, household heads are effectively the main decision-makers in agricultural production and are essentially farmers. Non-adopters reported spending relatively more labor days on their maize plots than adopters. The average age of the household head was 53.24 years, with a mean farming experience of 24.95 years, suggesting that farm heads in the study area are middle-aged and possess substantial agricultural experience. The average distance to the nearest market was 3.45 km, with adopters living closer to markets on average. The mean total farm size per household was 2.468 hectares, of which approximately 0.94 hectares were allocated to maize cultivation. Interestingly, non-adopters owned larger landholdings and devoted a greater proportion of their farmland to maize production; however, they harvested and sold smaller quantities of maize compared to adopters. Extension services, measured by the number of visits from agricultural agents, are designed to enhance the productivity and efficiency of rural farming systems. On average, households received 0.633 visits per month, with adopters reporting significantly more frequent contact with extension agents. Likewise, adopters applied higher quantities of chemical fertilizers to their maize plots than non-adopters. The observed statistical differences between adopters and non-adopters in key variables, including gender of the household head, labor days, distance to the nearest market, total farm size, maize plot size, soil fertility status, number of extension contacts, and fertilizer use, suggest potential hidden bias. These differences highlight the importance of applying the ESR model with instrumental variables to adequately control for selection bias and unobserved heterogeneity when estimating the true impact of STMV adoption on maize yield and household food security.

4. Empirical results and discussion

4.1. Determinants of adoption of stress-tolerant maize varieties

The maximum likelihood estimates of the probit model for the adoption of STMV are presented in Table 3. Marginal effects indicate the impact of a one-unit change in an exogenous variable on the probability of adoption. Goodness-of-fit measures suggest that the estimated models fit the data reasonably well. Likelihood ratio tests showed that the parameter estimates were statistically different from zero at a significance level of less than 1%. Overall, nine variables were found to be significant in explaining the adoption of STMV. These include male-headed households, number of labor days worked on the maize farm, livestock, size of total farmland owned by the household, quantities of maize harvested, distance to the nearest market, status of soil fertility, frequency of extension contact, and amount of chemical fertilizer applied. Male-headed households are more likely to adopt STMV compared to those headed by female. This result aligns with a previous study in Uganda, which found that male-headed households are more likely to use drought-tolerant maize varieties than female-headed households (Fisher et al. 2019). The probability of adopting STMV increases with the frequency of extension contact, highlighting the critical importance of farm households accessing relevant information and resources through extension agents in the study area when seeking to grow STMV. It is important to note that the magnitudes of the coefficients for 'extension contact' and 'distance to market' reported here differ slightly from those presented in the instrument falsification tests in Appendix Table A1. This difference is related to specification differences, as the selection equation aims not to perfectly explain adoption but to account for unobserved heterogeneity that could bias impacts on outcomes (Kabunga et al. 2012; Melesse et al. 2023).

4.2. Impact of stress-tolerant maize varieties on yield

This section examines the relationship between STMV adoption and maize yield. Detailed FIML estimates from the endogenous switching regression model are reported in Appendix Table A3 (column a). The results of the Wald test of independent equations indicate that the estimated coefficients of the random errors

Table 3. Probit model of estimates of determinants of adoption of STMVs.

Variables	Coefficient	Robust Std. Err	Marginal effect	Std. Err
Gender (male)	0.210**	0.124	0.076*	0.045
Age	0.000	0.004	0.000	0.001
Farm experience	−0.004	0.004	−0.001	0.001
Head education	−0.014	0.015	−0.005	0.005
Household size	0.006	0.025	0.002	0.008
Labor days	−0.004**	0.002	−0.015**	0.000
Livestock	−0.060**	0.028	−0.022**	0.010
Total farm	−0.073***	0.025	−0.026***	0.009
Maize harvested	0.032**	0.018	0.011**	0.006
Maize grain sold	0.013	0.035	0.004	0.130
Distance to input market	−0.037***	0.022	−0.024`***	0.007
Soil fertility	−0.238 **	0.119	−0.087*	0.043
Extension	0.023**	0.006	0.004**	0.022
Intercropping	−0.222	0.130	−0.081	0.047
Organic fertilizer	−0.000	0.000	−0.000	0.001
Chemical fertilizer	0.001***	0.001	0.001**	0.001
_cons	0.765	0.378***		
Log pseudolikelihood	= −346.20408			
Number of observations	= 540			
Wald chi2(17)	= 51.23			
Prob > chi2	= 0.0000			
Pseudo R2	= 0.0750			

Note: The results are significant at *** 1%, ** 5%, and *10% levels, respectively.

in the selection equation (η) and outcome equations (δ_i) are not jointly significant. This suggests the absence of a self-selection problem in our sample or that the self-selection for STMV adoption is weak. However, the correlation coefficients between the random errors of adopters and non-adopters are statistically significant, indicating an endogenous switching effect. Furthermore, these correlation coefficients have similar signs, suggesting that STMV adoption significantly affects the corresponding outcome for both adopters and non-adopters who eventually chose to adopt the technologies (Alene and Manyong 2007).

Table 4 presents the estimated treatment effects of STMV adoption on maize yield. The results show that adoption has a significant effect on yield. The expected yield for adopters of STMV was 5.765, while it was 5.490 for non-adopters. The observed difference in yield indicates that farmers who adopted STMV increased their maize yield by 0.275 q/ha, which is approximately 27.5% more than that of farmers who did not adopt. This result aligns with the findings of Katengeza and Holden (2020) in Malawi and Gebre, Mawia, et al. (2021) in Tanzania, who reported that the adoption of STMV increased maize yield by 5.47 and 10 q/ha, respectively. Moreover, recent studies by Kamara et al. (2024) and Kolapo et al. (2023) in Nigeria indicate that yield effects are larger for farmers with the highest propensity to adopt STMV. In the counterfactual scenario, adopters would have obtained a yield of 5.073 q/ha, while non-adopters would have achieved 7.877 q/ha, if they had adopted. ATT was positive and statistically significant, implying that adoption of STMV increased maize yield by 69.2%. This suggests that adopters would have lost an average of 0.692 q/ha of maize yield had they not adopted. On the other hand, the positive and statistically significant ATU indicates that farmers who did not adopt would have increased their maize yield by approximately 239% if they had adopted STMV – higher than the benefit observed among adopters. These results emphasize the need for properly targeted interventions to encourage the uptake of climate-resilient farming technologies in order to improve the agricultural productivity of smallholders in drought-prone areas.

The last row of Table 4 shows a highly significant and negative transitional heterogeneity (TH) for the outcome variable, suggesting that farmers who adopted and those who did not adopt STMV were systematically different. The negative TH implies that adopting STMV was more significant and beneficial for farming households that had not previously adopted it than for those who had.

The base heterogeneity (BH) effect for maize yield is also negative, indicating that unobservable

Table 4. ESR estimates of the effect of STMV adoption on yield, 2018 survey, Kenya.

		Mean values across decision stage in ESR		
Outcome variable	Sub-samples in ESR	Adopt	Not to adopt	Average treatment effect in ESRs
Maize Yield	Adopters (ATT)	(a) 5.765 (0.024)	(c) 5.073 (0.029)	ATT = 0.692***
	Non-adopters (ATU)	(d) 7.877 (0.038)	(b) 5.490 (0.035)	ATU = 2.387***
	Heterogeneity effects	$BH_1 = -2.112$	$BH_2 = -0.417$	TH = −1.695***

Notes: *** Statistically significant at the 1% level. ATT represents the average treatment effect on the treated, ATU denotes the average treatment effect on the untreated, and TH refers to heterogeneity effects. Standard errors are reported in parentheses.

heterogeneity plays a large role in affecting the maize yields of adopters. This suggests hierarchical sorting that favors adopters toward above-average outcomes, regardless of adoption status. However, adopters have a higher propensity to adopt STMV and benefit more from doing so than from not adopting (Alene and Manyong 2007; Di Falco et al. 2011; Melesse et al. 2023). This could be due to targeted distribution and donation of improved seed varieties, which is common during the early trial and dissemination phases of new varieties in Africa.

The results also reveal differences in the coefficients of the explanatory variables in the outcome equations for STMV adopters and non-adopters (Appendix Table A3, column a). Overall, several covariates are significant determinants of maize yield for both groups, although some show heterogeneous associations with maize yield between the two groups. Among STMV adopters, maize yield increases with the quantity of maize harvested, the quantity sold in the market, and the amount of chemical fertilizer applied to maize plots but decreases with the total farm size of the household.

Several studies have found a negative relationship between plot size and crop yield, often attributed to measurement errors such as systematic over-reporting of production on smaller plots and under-reporting on larger ones (Desier and Jolliffe 2018). However, a more recent study by Bevis and Barrett (2020) challenges this explanation, arguing that neither measurement error in plot size nor omitted variables drive the negative relationship. Instead, they propose an 'edge effect,' where crops growing along plot peripheries tend to yield more than those in the interior, making smaller plots relatively more productive, as a larger share of their area falls along the perimeter.

Conversely, Njuki et al. (2006) suggest that the inverse relationship between farmland size and productivity in Kenya is due to limited access to and the relatively high cost of agricultural inputs. As farmers cultivate larger areas, they are less able to apply sufficient inputs to maintain productivity (Gebre, Isoda, et al. 2021). The implications of the present results align with the findings of Njuki et al. (2006). For non-adopters, maize yield increases with the age of the household head, the quantity of maize harvested and sold, intercropping, and the frequency of extension contacts, while it decreases with the number of livestock owned.

4.3. Impact of stress tolerant maize adoption on food security

Results on the impact of adopting STMV on household food security outcomes (Table 5) show that adoption of STMV reduces households' vulnerability to food (access) insecurity by 35.4% compared with the counterfactual scenario of non-adoption. Similarly, adoption of STMV increases the average probability of food being secure by about 22.3% points for adopters relative to the counterfactual of non-adoption. At the same time, on average, non-adopters would have reduced their vulnerability to food (access) insecurity by about 62% points had they adopted STMV. They also would have increased their average probability of being food secure by about 44% points had they adopted STMV. This suggests that the improvement in food security for non-adopters, had they adopted STMV, is greater than the loss in food security that adopters would have experienced had they not adopted STMV. It also implies that non-adopters have forgone substantial benefits due to their failure to adopt the technology. Therefore, significant food security gains could be realized through further promotion of STMV adoption and by addressing barriers that hinder adoption among non-adopters. These findings are consistent with previous studies by Jaleta et al. (2018), G. G. Gebre, H. Mawia, et al. (2021), Radeny et al. (2022), and Melesse et al. (2023) conducted in Ethiopia, Tanzania, Kenya, and Nigeria, respectively. Detailed FIML estimations from the two endogenous switching regressions for food security outcomes are presented in Appendix Table A3 (columns b and c).

The estimated MTE, which accounts for unobserved heterogeneity within the sampled population, indicates that vulnerability to food insecurity decreases with the propensity to adopt STMV (Figure 1(a)). The MTE curve in Figure 1(a) is downward sloping, with positive treatment effects above zero at the lower end of the unobserved resistance distribution, eventually declining to negative effects below zero at the right end of the distribution. This implies an ATE of approximately −0.501, and the downward-sloping pattern is consistent with positive selection on unobservable gains, as predicted by a simple Roy model (Andresen, 2018).

Table 5. Effects of STMVs on household food security: endogenous switching Poisson and Probit regressions.

	Treatment effects			
Outcome	ATT	ATU	ATE	MTE
HFIAS Score	−0.354(1.577)***	−0.620(1.244)***	−0.501(1.495)***	−0.348(1.192)***
Food secure	0.223(0.227)***	0.439(0.157)***	0.343(0.191)***	0.405(0.040)***

Notes: ATT – Average Treatment Effect on the Treated, ATU – Average Treatment Effect on the Untreated, ATE – Average Treatment Effect, and MTE – Marginal Treatment Effect; Bootstrapped standard errors in parentheses; ***$p < 0.01$.

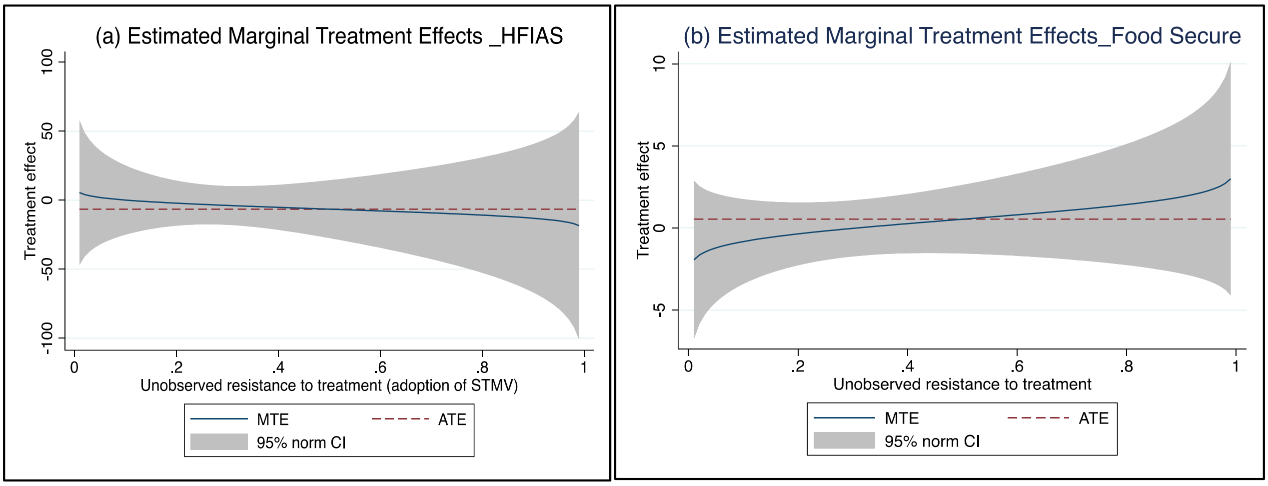

Figure 1. MTE curves for household food security.

Lower levels of unobserved resistance to treatment are associated with higher vulnerability to food insecurity, but vulnerability tends to decrease as unobserved resistance increases. Figure 1(b) presents the MTE curve for the food-secure status of the sampled households. This curve is upward sloping, with negative treatment effects at the lower end of the unobserved resistance distribution, which gradually increases to positive effects at the higher end. This suggests that the food-secure status of farm households increases with the propensity to adopt STMV. These results imply that adopters have lower food security than non-adopters at low levels of propensity to adopt STMV, while at higher levels of propensity, adopters have greater food security than non-adopters. This supports the heterogeneous treatment effect framework, which sometimes reveals that certain adopters experience worse outcomes than non-adopters due to unobserved characteristics. This finding reflects that farmers more likely to adopt STMV benefit more from adoption, while those less likely to adopt are better off than average in the untreated state. This aligns with the concept of adoption based on comparative advantage (Suri 2011). Our findings are consistent with those of a similar study by Kamara et al. (2024) in Nigeria.

Finally, the results reveal differences in the coefficients of the explanatory variables in the outcome equations for STMV adopters and non-adopters, with respect to both HFIAS and the binary food security outcomes (Appendix Table A3, columns a and c). For adopters, HFIAS decreases with the educational level of the household head, the number of livestock owned, total farmland size, and distance to the nearest market. In contrast, it increases with household size, the amount of maize grain sold, and the quantity of organic fertilizer applied to maize plots. Similarly, the food security status of adopters improves with the number of livestock and distance to the nearest market. Adopters who practice intercropping are also less likely to experience food insecurity (lower HFIAS) and more likely to be food secure. However, the probability of achieving food-secure status declines with household size. For non-adopters, HFIAS decreases in male-headed households, and with higher livestock holdings, greater maize harvests, and the use of intercropping practices. Conversely, it increases with household size, the amount of organic fertilizer applied, and the distance to the nearest market. Among non-adopters, the likelihood of being food secure rises with the number of livestock but declines with household size.

5. Conclusion and policy implications

This study demonstrates the significant potential of STMV adoption in enhancing both maize yield and household food security among smallholder farmers in Kenya. The findings show that adopters achieved 27.5% higher yields than non-adopters, with counterfactual analysis indicating that non-adopters could realize yield gains of up to 239% if they adopted. Similarly, adoption reduced vulnerability to food insecurity by 35.4% and increased the probability of being food secure by 22.3%, with even larger potential benefits for current non-adopters. These results reveal a substantial untapped opportunity to improve household welfare through broader dissemination of STMV.

The analysis further highlights considerable heterogeneity: while current adopters already benefit, the largest unrealized gains lie among non-adopters. Key drivers of adoption include male headship, frequent extension contact, the quantity of chemical fertilizer used, and higher maize production, whereas barriers such as the number of labor days spent on maize plots, livestock ownership, large farm size, distance to markets, and high soil fertility constrain STMV uptake.

These findings underscore the transformative potential of STMV for strengthening resilience in drought-prone regions while revealing persistent gaps in access and adoption. For policy and practice, the results suggest three priorities: (i) scaling extension services and farmer training to broaden awareness and knowledge of STMV, (ii) improving input delivery systems and market access to reduce adoption barriers, and (iii) developing gender-sensitive approaches to close adoption gaps faced by female-headed households. By addressing these constraints, governments and development partners can unlock the large productivity and food security gains currently forgone by non-adopters, thereby accelerating progress toward climate-resilient agriculture and rural food security, while contributing to the achievement of critical Sustainable Development Goals, including 'No Poverty,' 'Zero Hunger,' and 'Climate Action' for Kenya and beyond.

Note

1. *An adopter of a STMV is defined as a farmer who cultivated STMV during 2018 cropping season.*

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Ethical approval

This study does not involve human subjects.

Consent to participate

Verbal informed consent was obtained prior to the interview

Data availability statement

Data is available upon reasonable request

References

Abate D, Tesfaye H, Kassaw M, Addis Y, Mossie H. 2023. Impact of adopting the climate-smart crop varieties on food security in Southwestern Ethiopia. Afr J Sci Technol Innov Dev. 15(5):590–598. https://doi.org/10.1080/20421338.2022.2157787

Abdulai A, Huffman W. 2014. The adoption and impact of soil and water conservation technology: an endogenous switching regression application. Land Econ. 90(1):26–43. https://doi.org/10.3368/le.90.1.26

Adéchian SA, Baco MN, Tahirou A. 2023. Improving the adoption of stress tolerant maize varieties using social ties, awareness or incentives: insights from northern Benin (West-Africa)'. World Devel Sustainability. 3:100112. https://doi.org/10.1016/j.wds.2023.100112

Adu GB et al. 2021. Trait profile of maize varieties preferred by farmers and value chain actors in northern Ghana. Agron Sustain Dev. 41(4). https://doi.org/10.1007/s13593-021-00708-w

Alene AD, Manyong VM. 2007. The effects of education on agricultural productivity under traditional and improved technology in northern Nigeria: an endogenous switching regression analysis. Empir Econ. 32(1):141–159. https://doi.org/10.1007/s00181-006-0076-3

Andresen ME, 2018. Exploring marginal treatment effects: flexible estimation using Stata. stata J Promoting Commun Stat Stata. 18(1):118–158. https://doi.org/10.1177/1536867X1801800108

Bevis LE, Barrett CB. 2020. Close to the edge: high productivity at plot peripheries and the inverse size-productivity relationship. J Dev Econ. 143:1–15. https://doi.org/10.1016/j.jdeveco.2019.102377

Cairns JE, Prasanna BM. 2018. Developing and deploying climate-resilient maize varieties in the developing world. Curr Opin In Plant Biol. 45:226–230. https://doi.org/10.1016/j.pbi.2018.05.004

Christophe AK, Anatole GA, Henning CH, Saer S. 2020. Estimating the impact of agricultural cooperatives in Senegal: propensity score matching and endogenous switching regression analysis. No. WP2020-10'.

Coates J, Swindale A, Bilinsky P. 2007. Household food insecurity access Scale (HFIAS) for measurement of food access: indicator guide. Vol 13. Food and Nutrition Technical Assistance Project, Academy for Educational Development.

Desier S, Jolliffe D. 2018. Land productivity and plot size: is measurement error driving the inverse relationship? J Dev Econ. 130:84–98. https://doi.org/10.1016/j.jdeveco.2017.10.002

Di Falco S, Veronesi M, Yesuf M. 2011. Does adaptation to climate change provide food security? A micro perspective from Ethiopia. Am J Agri Econ. 93(3):829–846. https://doi.org/10.1093/ajae/aar006

Dontsop Nguezet PM et al. 2020. Are farmers using cropping system intensification technologies experiencing poverty reduction in the Great Lakes region of Africa? Food And Energy Secur. 9(3). https://doi.org/10.1002/fes3.205

Fisher M et al. 2015. Drought tolerant maize for farmer adaptation to drought in sub-Saharan Africa: determinants of adoption in eastern and southern Africa. Clim Change. 133(2):283–299. https://doi.org/10.1007/s10584-015-1459-2

Fisher M, Habte E, Ekere W, Abate T, Lewin P. 2019. Reducing gender gaps in the awareness and uptake of drought-tolerant maize in Uganda: the role of education, extension services and social networks. J. Gend. Agric. Food Secur. (Agri-Gend). 4:38–50.

Gebre GG, Isoda H, Rahut DB, Amekawa Y, Nomura H. 2019. Gender differences in the adoption of agricultural technology: the case of improved maize varieties in southern Ethiopia. Women's Stud Int Forum. 76:102264. https://doi.org/10.1016/j.wsif.2019.102264

Gebre GG, Isoda H, Rahut DB, Amekawa Y, Nomura H. 2021. Gender differences in agricultural productivity: evidence from maize farm households in Southern Ethiopia. GeoJournal. 86(2):843–864. https://doi.org/10.1007/s10708-019-10098-y

Gebre GG, Mawia H, Makumbi D, Rahut BD. 2021. The impact of adopting stress-tolerant maize on maize yield, maize income, and food security in Tanzania '. Food Energy Secur. 10(4). https://doi.org/10.1002/fes3.313

Hasebe T. 2020. Endogenous switching regression model and treatment effects of count-data outcome. The Stata J. 20 (3):627–646. https://doi.org/10.1177/1536867X20953573

Headey DD, Ecker O. 2012. Improving the measurement of food security. Ifpri discussion paper no. 01225'.

Jaleta M, Kassie M, Marenya P, Yirga C, Erenstein O. 2018. Impact of improved maize adoption on household food security of maize producing smallholder farmers in Ethiopia. Food Secur. 10(1):81–93. https://doi.org/10.1007/s12571-017-0759-y

Kabunga NS, Dubois T, Qaim M. 2012. Yield effects of tissue culture bananas in Kenya: accounting for selection bias and the role of complementary inputs. J Agric Econ. 63 (2):444–464. https://doi.org/10.1111/j.1477-9552.2012.00337.x

Kamara AY et al. 2024. Beyond average: are the yield and income impacts of adopting drought-tolerant maize varieties heterogeneous? '. Clim And Devel. 16(1):67–76. https://doi.org/10.1080/17565529.2023.2178840

Katengeza PS, Holden TS. 2020. Productivity impact of drought tolerant maize varieties under rainfall stress in Malawi: a continuous treatment approach. Agric Econ. 52 (1):157–171. https://doi.org/10.1111/agec.12612

Kolapo A et al. 2023. Adoption of drought tolerant maize varieties and farmers' access to credit in Nigeria: implications on productivity '. Sustain Futur. 6:100142. https://doi.org/10.1016/j.sftr.2023.100142

Lokshin M, Glinskaya E. 2009. The effect of male migration on employment patterns of women in Nepal. World Bank Econ Rev E. 23(3):481–507. https://doi.org/10.1093/wber/lhp011

Lokshin M, Sajaia Z. 2004. Maximum likelihood estimation of endogenous switching regression models. The Stata J. 4 (3):282–289. https://doi.org/10.1177/1536867X0400400306

Lokshin M, Sajaia Z. 2011. Impact of interventions on discrete outcomes: maximum likelihood estimation of the binary choice models with binary endogenous regressors. The Stata J. 11(3):368–385. https://doi.org/10.1177/1536867X1101100303

Lunduka RW, Mateva KI, Magorokosho C, Manjeru P. 2019. Impact of adoption of drought-tolerant maize varieties on total maize production in South Eastern Zimbabwe. Clim And Devel. 11(1):35–46. https://doi.org/10.1080/17565529.2017.1372269

Maddala GS. 1983. Limited dependent and qualitative variables in econometrics. Cambridge University Press.

Melesse MB, Cecchi F. 2017. Does market experience attenuate risk aversion? Evidence from landed farm households in Ethiopia. World Devel. 98:447–466. https://doi.org/10.1016/j.worlddev.2017.05.011

Melesse MB, Miriti P, Muricho G, Ojiewo CO, Afari-Sefa V. 2023. Adoption and impact of improved groundnut varieties on household food security in Nigeria. J Agric Food Sys Community Dev And Food Res. 14:100817. https://doi.org/10.1016/j.jafr.2023.100817

Njuki M, Kihiyo M, Oktingati A, Place F. 2006. Productivity differences between male and female managed farms in the eastern and central highlands of Kenya. Contributed paper prepared for presentation at the International Association of Agricultural Economists Conference; [2006 Aug 12–18]; Gold Coast, Australia.

Obunyali CO et al. 2024. Efficacy of event MON 87460 in drought-tolerant maize hybrids under optimal and managed drought-stress in Eastern and Southern Africa. J Genet Eng Biotechnol. 22(1):100352. https://doi.org/10.1016/j.jgeb.2024.100352

Radeny M, Rao EJO, Ogada MJ, Recha JW, Solomon D. 2022. Impacts of climate-smart crop varieties and livestock breeds on the food security of smallholder farmers in Kenya. Food Sec. 14(6):1511–1535. https://doi.org/10.1007/s12571-022-01307-7

Shiferaw B, Kassie M, Jaleta M, Yirga C. 2014. Adoption of improved wheat varieties and impacts on household food security in Ethiopia. Food Policy. 44:272–284. https://doi.org/10.1016/j.foodpol.2013.09.012

Simtowe F et al. 2019. Heterogeneous seed access and information exposure: implications for the adoption of drought-tolerant maize varieties in Uganda. Agric Econ. 7 (1). https://doi.org/10.1186/s40100-019-0135-7

Simtowe F, Makumbi D, Worku M, Mawia H, Rahut DB. 2021. Scalability of adaptation strategies to drought stress: the case of drought tolerant maize varieties in Kenya. Int J Agric Sustain. 19(1):91–105. https://doi.org/10.1080/14735903.2020.1823699

Simtowea F et al. 2019. Impacts of drought-tolerant maize varieties on productivity, risk, and resource use: evidence from Uganda. Land Use Policy. 88:104091. https://doi.org/10.1016/j.landusepol.2019.104091

Suri T. 2011. Selection and comparative advantage in technology adoption. Econometrica. 79:159–209.

Tesfaye W, Tirivayi N. 2018. The impacts of postharvest storage innovations on food security and welfare in Ethiopia. Food Policy. 75:52–67. https://doi.org/10.1016/j.foodpol.2018.01.004

Voss RC, Donovan J, Rutsaert P, Cairns JE. 2021. Gender inclusivity through maize breeding in Africa: a review of the issues and options for future engagement. Outlook Agric. 50(4):392–405. https://doi.org/10.1177/00307270211058208

Walker TS, Alwang J. 2015. Crop improvement, adoption and impact of improved varieties in food crops in sub-Saharan Africa. Cabi.

Wanjira JK et al. 2022. Impact of climate-smart maize varieties on household income among smallholder farmers in Kenya: the case of Embu County. Afr J Agric Resource Econ. 17(3):224–238. https://doi.org/10.53936/afjare.2022.17(3).15

Worku M et al. 2020. On-farm performance and farmers' participatory assessment of new stress tolerant maize hybrids. Field Crops Res. 246:107693. https://doi.org/10.1016/j.fcr.2019.107693

Wossen T et al. 2017. Measuring the impacts of adaptation strategies to drought stress: the case of drought tolerant maize varieties. J Environ Manag. 203:106–113. https://doi.org/10.1016/j.jenvman.2017.06.058

Appendix

Table A1. Instrument falsification tests on the validity of the selection instruments (parameter estimates).

Variables	Selection into STMV intervention (Probit)	Maize Yield (OLS)	HFIAS score (Poisson)	Food secure (Probit)
Instruments				
Distance from input market	−0.068(0.022)***	0.008(0.012)	−0.030(0.024)**	0.051(0.028)**
Extension	0.012(0.006)***	0.147 (0.063)**	−0.022(0.082)	0.002(0.081)
Controls	Yes	Yes	yes	Yes
Constant	0.765 (0.378)**	5.326 (0.547)***	0.678(0.484)	0.043(0.577)
X^2	55.04***		125.68***	29.03**
F		3.37		
Observations	540	273	273	273

Notes: The outcomes (Maize Yield, HFIAS score, and Food secure) are for non-adopters. All control variables are included in the models, but parameters are not reported to save space. Standard errors reported in parentheses. STMV – Stress Tolerant Maize Variety; HFIAS – Household Food Insecurity Access Scale. $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A2. Household Food Insecurity Access Scale (HFIAS) measurement tool.

No.	Content of the questions
1	In the past four weeks, did you worry that your household would not have enough food? 1 = yes, 0 = no (skip Q2). If yes, how often did this happen? Codes: 1 = Rarely (once or twice in the past four weeks), 2 = Sometimes (3–10 times in the past four weeks), 3 = Often (more than 10 times in the past four weeks)
2	In the past four weeks, have you or any household member were not able to eat the kinds of foods you preferred because of a lack of resources? 1 = yes, 0 = no (skip Q2). If yes, how often did this happen? Codes: 1 = Rarely (once or twice in the past four weeks), 2 = Sometimes (3–10 times in the past four weeks), 3 = Often (more than 10 times in the past four weeks)
3	In the past four weeks, did you or any household member have to eat a limited variety of foods due to a lack of resources? 1 = yes, 0 = no (skip Q2). If yes, how often did this happen? Codes: 1 = Rarely (once or twice in the past four weeks), 2 = Sometimes (3–10 times in the past four weeks), 3 = Often (more than 10 times in the past four weeks)
4	In the past four weeks, did you or any household member have to eat some foods that you really did not want to eat because of a lack of resources to obtain other types of food? 1 = yes, 0 = no (skip Q2). If yes, how often did this happen? Codes: 1 = Rarely (once or twice in the past four weeks), 2 = Sometimes (3–10 times in the past four weeks), 3 = Often (more than 10 times in the past four weeks)
5	In the past four weeks, did you or any household member have to eat a smaller meal than you felt you needed because there was not enough food? 1 = yes, 0 = no (skip Q2). If yes, how often did this happen? Codes: 1 = Rarely (once or twice in the past four weeks), 2 = Sometimes (3–10 times in the past four weeks), 3 = Often (more than 10 times in the past four weeks)
6	In the past four weeks, did you or any household member have to eat fewer meals in a day because there was not enough food? 1 = yes, 0 = no (skip Q2). If yes, how often did this happen? Codes: 1 = Rarely (once or twice in the past four weeks), 2 = Sometimes (3–10 times in the past four weeks), 3 = Often (more than 10 times in the past four weeks)
7	In the past four weeks, was there ever no food to eat of any kind in your household because of a lack of resources to get food? 1 = yes, 0 = no (skip Q2). If yes, how often did this happen? Codes: 1 = Rarely (once or twice in the past four weeks), 2 = Sometimes (3–10 times in the past four weeks), 3 = Often (more than 10 times in the past four weeks)
8	In the past four weeks, did you or any household member go to sleep at night hungry because there was not enough food? 1 = yes, 0 = no (skip Q2). If yes, how often did this happen? Codes: 1 = Rarely (once or twice in the past four weeks), 2 = Sometimes (3–10 times in the past four weeks), 3 = Often (more than 10 times in the past four weeks)
9	In the past four weeks, did you or any household member go a full day and night without eating anything because there was not enough food? 1 = yes, 0 = no (skip Q2). If yes, how often did this happen? Codes: 1 = Rarely (once or twice in the past four weeks), 2 = Sometimes (3–10 times in the past four weeks), 3 = Often (more than 10 times in the past four weeks)

Table A3. Full information maximum likelihood estimates of the endogenous switching regression models.

	(a) Maize Yield		(b) Household Food Insecurity Access Scale		(c) Food Secure	
Variables	Adopter	Non-adopter	Adopter	Non-adopter	Adopter	Non-adopter
Gender	−0.055(0.167)	0.251(0.196)	0.126(0.117)	0.472(0.153)**	−0.109(0.162)	−0.270(0.185)
Age	0.001(0.004)	0.010(0.006)*	−0.005(0.003)	−0.010(0.006)	0.006(0.004)	0.002(0.005)
Farm experience	0.005(0.004)	−0.0070.006)	0.001 (0.004)	0.002(0.005)	0.002 (0.004)	−0.003(0.004)
Head education	0.002(0.019)	−0.021(0.024)	−0.052(0.014)***	0.006(0.011)	0.009 (0.018)	−0.007(0.020)
Household size	0.021(0.032)	0.022(0.038)	0.157(0.027)***	0.130(0.024)***	−0.058(0.036)**	−0.071(0.035)**
Labor days	0.002(0.002)	−0.004(0.002)	0.002(0.001)	−0.003(0.001)	−0.004(0.002)	0.001(0.002)
Livestock	0.057(0.045)	−0.099(0.043)**	−0.282(0.084)***	−0.217(0.046)***	0.101(0.062)***	0.084 (0.044)**
Total farm	−0.079(0.041)**	−0.014(0.023)	−0.054(0.017)**	0.022(0.010)	−0.085(0.038)	−0.017(0.022)
Maize harvested	0.051(0.024)**	0.126(0.027)***	0.011(0.014)	−0.049(0.008)***	0.021(0.022)	−0.010 (0.024)
Maize grain sold	0.152(0.042)***	0.222(0.062)***	0.035(0.013)**	−0.022(0.020)	−0.082(0.054)	−0.013(0.050)
Soil fertility	0.146(0.159)	−0.073(0.194)	0.036(0.137)	0.230(0.177)	0.114(0.152)	−0.179(0.165)
Intercropping	0.197(0.162)	0.430(0.214)**	−0.483(0.105)***	−0.470(0.183)***	0.558(0.183)**	0.215(0.206)
Organic fertilizer	−0.000(0.000)	−0.000(0.000)	0.000(0.000)***	0.000(0.000)***	−0.000(0.000)	−0.000 (0.000)
Chemical fertilizer	0.004(0.002)**	−0.000(0.000)	−0.003(0.001)	0.000(0.000)	0.000(0.002)	−0.005(0.002)**
Extension	0.008(0.008)	0.178(0.091)**	–	–	–	–
Distance from market	–	–	−0036(0.012)***	−0.054(0.024)**	0.028(0.016)**	0.035(0.032)
_cons	0.116(0.065)***	0.508(0.044)***	−0.230(0.192)	0.701(0.526)	−0.043(0.454)	0.785(0.661)
/lnsigma (0/1)	0.523(0.081)***	0.161(0.066)***	0.484(0.073)**	0.448(0.133)***		
/athrho(0/1)	1.403(0.260)***	−0.405(0.227)***	−0.088(0.119)**	0.046(0.192)**	0.430(0.907)	−2.019(26.443)
sigma(0/1)	1.687(0.137)**	1.174(0.078)**	1.623(0.119)**	1.565(0.209)**		
rho(0/1)	0.886(0.055)	0.384(0.194)	0.088 (0.118)	0.046(0.192)	0.432(0.267)	0.555(0.345)
Test of independent equation	1.52		0.73		0.85	
Wald chi2 p-value	0.351		0.611		0.804	
Observations	267	273	267	273	267	273

Note: Standard errors are reported in parentheses. The results are significant at ***1%, **5%, and *10% levels, respectively.