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Climate-smart agriculture and multidimensional poverty among smallholder maize farmers in Kenya

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Abstract

Climate-smart agriculture (CSA) has emerged as a central strategy for strengthening agricultural resilience under climate change. However, limited evidence exists on whether adopting multiple CSA practices is associated with improved multidimensional poverty among smallholder farmers. This study examined the association between CSA adoption intensity and multidimensional poverty among smallholder maize-farming households in Kenya. CSA intensity was measured as the number of CSA practices adopted by each household and categorised into high- and low-intensity adoption groups. An endogenous switching regression model was employed to account for potential selection associated with households' adoption decisions, while propensity score matching was used as a robustness check based on observable characteristics. The findings reveal that CSA adoption remains relatively low, with over half of the sampled households not adopting any of the selected CSA practices and less than one percent adopting three practices simultaneously. After accounting for observed household characteristics and potential selection, households with higher CSA intensity exhibited lower scores on the multidimensional poverty index (MPI) than households with lower intensity. Education, farmer group membership and household experience were also consistently associated with lower MPI levels, while substantial spatial heterogeneity was observed across counties. The findings suggest that promoting the integrated adoption of complementary CSA practices, alongside investments in extension services, farmer organisations and improved access to finance, could help reduce household MPI levels. By linking climate adaptation with multidimensional poverty, this study provides evidence to inform the design of more targeted and inclusive CSA policies in Kenya and similar smallholder farming systems.

Key words: climate change, multidimensional poverty, climate-smart agriculture, adoption intensity, productivity

1. Introduction

1.1 Background information

Climate change is increasingly challenging efforts to achieve sustainable agricultural development and poverty reduction in smallholder farming systems where livelihoods depend heavily on climate-sensitive agriculture (Abhilash *et al*. 2021; Ndung'u *et al*. 2023; Ince-Palamutoğlu 2026). Across sub-Saharan Africa, rising temperatures, erratic rainfall, prolonged droughts and increasing incidences of pests and diseases continue to undermine agricultural productivity (Molua *et al*. 2010; Fentie & Beyene 2019; Dushimiyimana *et al*. 2026). These challenges reduce agricultural output and weaken farmers' resilience to climate shocks. As climate-related risks intensify, strengthening the resilience of smallholder farming systems has become central to achieving sustainable agricultural development and the Sustainable Development Goals (World Bank 2021).

Climate-smart agriculture (CSA) has gained considerable attention as a sustainable approach to enhancing agricultural productivity, strengthening resilience to climate change, and contributing to climate change mitigation (Erenstein *et al*. 2022; Muriithi *et al*. 2023). Consequently, governments and development partners have increasingly promoted CSA technologies and practices across developing countries. In Kenya, these efforts have been supported through national and donor-funded initiatives, including the Kenya Climate Smart Agriculture Project (KCSAP) and Sustainable Land Management programmes (Ndung'u *et al*. 2023). Financial constraints, limited access to extension services and credit, inadequate technical knowledge and the high cost of implementing some CSA practices continue to constrain widespread adoption (FAO 2020; Molua 2022).

Despite growing policy support for CSA, its contribution to poverty reduction remains uncertain. Previous studies consistently associate CSA adoption with higher agricultural productivity, improved food security and increased farm income (Priyadarshini & Abhilash 2020; Erenstein *et al*., 2022). However, evidence of its effect on MPI remains limited and inconclusive. Some studies report positive welfare effects following CSA adoption (Lipper *et al*. 2014; Tsegaye 2020; Habtewold 2021), Others find limited or mixed impacts due to high adoption costs, labour requirements, institutional constraints and agroecological differences (Thornton *et al*. 2018). These inconsistent findings raise an important question: does greater adoption of CSA practices translate into lower MPI among smallholder farming households?

Similarly, important conceptual, empirical and methodological gaps remain. First, most studies conceptualise CSA adoption as a binary decision by comparing adopters and non-adopters (Jayne *et al*. 2019; Ali *et al*. 2022; Yitbarek & Tesfaye 2022; Islam & Farjana 2024). Such an approach overlooks the fact that farmers often adopt multiple CSA practices simultaneously. Consequently, MPI outcomes may depend on whether farmers adopt CSA and the extent of adoption. Because different CSA practices address distinct production constraints, adopting complementary practices may generate greater welfare gains than relying on a single practice.

In addition, existing studies predominantly evaluate the effects of CSA adoption on indicators such as agricultural productivity, farm income, consumption expenditure or food security, giving relatively limited attention to MPI (Okumu 2018; Nyberg *et al*. 2020; Hughes *et al*. 2020; Kogo *et al*. 2021; Mucheru-Muna *et al*. 2021). Thus, evaluating welfare through the lens of multidimensional poverty is particularly important because rural poverty extends beyond income deprivation to encompass deficits in education, health, housing conditions and access to basic services.

Methodological challenges continue to constrain causal inference in the CSA literature because farmers self-select into adopting climate-smart practices. Consequently, adopters and non-adopters may differ systematically in both observable and unobservable characteristics, potentially biasing the estimated impacts. To address this, the study employs endogenous switching regression to account for selection arising from observable and unobservable factors, complemented by propensity score matching as a robustness check to strengthen the credibility of the estimated treatment effects (Ali *et al*. 2022; Yitbarek & Tesfaye 2022; Islam & Farjana 2024).

Against this background, this study examines the effect of CSA adoption intensity on MPI among smallholder maize-farming households in Kenya using nationally representative data from the Kenya Climate Smart Agriculture Project (KCSAP) survey. The CSA practices under consideration for this study include irrigation, integrated manure management, integrated soil management, agroforestry and conservation agriculture. These practices were selected because they are among the principal CSA technologies promoted under the KCSAP and are consistently captured in the KCSAP household survey. Furthermore, they represent the three core pillars of CSA: enhancing agricultural productivity, strengthening resilience and adaptation to climate change (FAO 2013).

The study makes three contributions. First, it shifts the focus from binary adoption to the intensity of CSA adoption, providing evidence of whether adopting multiple CSA practices yields better multidimensional poverty outcomes. Second, it evaluates welfare using multidimensional poverty rather than conventional monetary indicators. Third, by combining endogenous switching regression and propensity score matching, the study provides more robust evidence of the relationship between CSA adoption intensity and MPI, while accounting for both observable and unobservable sources of selection.

1.2 Literature review

CSA has emerged globally as a key strategy for simultaneously enhancing agricultural productivity, strengthening resilience and improving rural livelihoods (Molua 2022; Muriithi *et al*. 2023; Ndung'u *et al*. 2023). However, adoption patterns remain highly heterogeneous across regions, reflecting differences in agro-ecological conditions, institutional frameworks, market access and the socioeconomic characteristics of farmers (Lipper *et al*. 2014; Abhilash *et al*. 2021; Muriithi *et al*. 2023).

For instance, farmers in West and Central Africa mainly adopt conservation agriculture, crop rotation, agroforestry and organic manure management because these practices align with traditional farming systems and require relatively low external inputs (Zossou *et al*. 2020; Molua & Ayuk 2021; Sanogo *et al*. 2023). In contrast, Eastern Africa adopts a broader mix of CSA practices, including drought-tolerant varieties, irrigation, agroforestry, and soil and water conservation, driven by greater climate variability and unpredictable rainfall (Molua 2012; Kassa & Abdi 2022; Kifle *et al*. 2022; Ndung'u *et al*. 2023).

Similarly, empirical evidence consistently identifies access to extension services, education, farm income, credit, social capital, farm size and climate information as key drivers of CSA adoption (Mujeyi *et al*. 2021; Ndung'u *et al*. 2023; Ma & Rahut 2024;). Household characteristics, including age, gender of the household head and labour availability also influence adoption decisions by shaping farmers' capacity to access information, mobilise resources and implement climate-smart practices (Kassa & Abdi 2022; Kifle *et al*. 2022; Sanogo *et al*. 2023). Collectively, these findings suggest that CSA adoption is determined by a complex interaction of economic, institutional and demographic factors that should be considered when assessing its welfare implications.

In addition, a substantial body of empirical evidence suggests that CSA adoption improves household poverty outcomes through multiple pathways. To begin with, CSA practices increase agricultural productivity and farm income by improving soil quality, enhancing input-use efficiency and reducing exposure to climate-related production risks (Molua *et al*. 2010; Maguza-Tembo *et al*. 2016; Asante *et al*. 2024). These productivity gains are often accompanied by improvements in food security, dietary diversity and household resilience, particularly in climate-vulnerable regions. Thus, CSA contributes positively to both the production and consumption dimensions of household welfare. However, whether these welfare gains translate into reductions in multidimensional poverty remains under-explored.

Despite the generally positive evidence, the welfare effects of CSA remain far from conclusive. While many studies report significant improvements in household welfare following CSA adoption, others find weak or statistically insignificant effects on income and food security (Lipper *et al*. 2014; Priyadarshini & Abhilash 2020; Habtewold 2021; Erenstein *et al*. 2022; Akpan & Zikos 2023). These inconsistencies have been attributed to differences in agroecological conditions, market access, institutional support, gender and the costs associated with adopting CSA practices (Molua 2012; Molua & Ayuk 2021). Consequently, the relationship between CSA adoption and household MPI remains context-dependent and warrants further investigation.

Taken together, the existing literature demonstrates that CSA has the potential to improve agricultural productivity and household welfare. However, important questions remain regarding whether adopting a broader portfolio of CSA practices is associated with lower MPI, whether these relationships hold at the national level among smallholder maize farmers, and whether previous empirical studies adequately account for farmers' self-selection into adoption. Addressing these gaps provides the motivation for the present study.

Figure 1 presents the conceptual framework underpinning this study. The underlying premise is that farmers adopting multiple complementary practices are more likely to achieve greater improvements in farm performance than those adopting few or no practices.

The framework proposes that greater CSA intensity improves agricultural outcomes by increasing productivity, resource-use efficiency and resilience to climate variability. These gains reduce MPI through two pathways: higher marketed production increases farm income, enabling investment in education, health care, housing and other basic needs, while production retained for household consumption improves food security and nutrition. Together, these pathways enhance household welfare and reduce MPI.

The framework further recognises that CSA adoption is not a random decision. Household characteristics, farm characteristics, institutional support, and market and environmental conditions jointly influence both the decision to adopt CSA practices and household welfare outcomes. These factors therefore act as confounding variables and are controlled for in the empirical analysis.

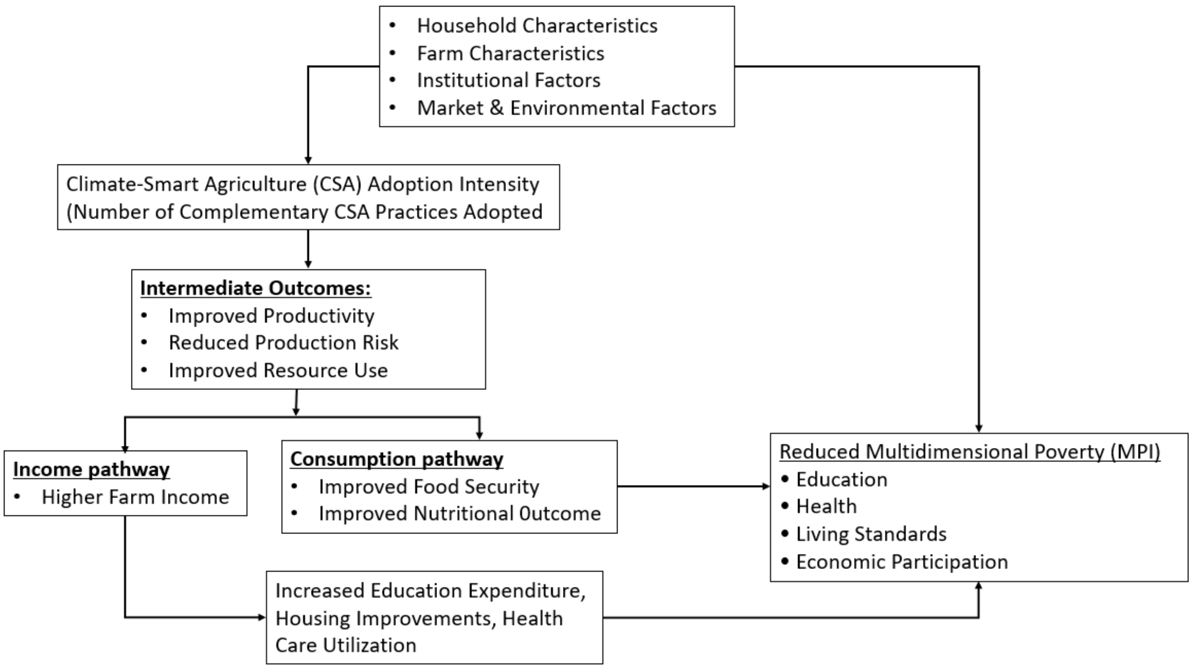

Figure 1: Conceptual framework of the association between climate-smart agriculture, adoption intensity and poverty

2. Methodology

2.1 Data and data sources

This study uses household-level data from the Kenya Climate-Smart Agriculture Project (KCSAP) survey conducted in 2020 and 2021 by the Tegemeo Institute of Agricultural Policy and Development in collaboration with the Ministry of Agriculture, Livestock, Fisheries and Cooperatives. The survey covered nine KCSAP counties, namely Marsabit, Nyandarua, Nyeri, Garissa, West Pokot, Uasin Gishu, Baringo, Siaya and Kisumu. These counties were purposively selected to capture diverse agroecological and socioeconomic contexts. Within these counties, a multistage sampling design was employed to select sub-counties, wards, villages and households, ensuring that the sampled households were representative of the target population within the selected counties. The sample size for this study was 8 091 households.

2.2 Measuring the multidimensional poverty index

The study adopted the Alkire-Foster (AF) methodology to measure the MPI for each household under consideration (Alkire & Foster 2011). The dimensions employed are standards of living, health, education and income potential. Each dimension is given an equal weight of 0.25 for transparency and simplicity for straightforward communication of the structure of the index to the public and policymakers for better understanding and acceptance. Below are the dimensions, indicators and their respective weights.

Table 1: Dimensions, indicators and weights

Dimension	Weight	Indicator	Deprivation cut-off	Weight
Health	0.25	Nutrition	Household skipped at least one meal/reported inadequate nutrition	0.125
		Access to health care	No access to a health facility or travel time exceeds 30 minutes	0.125
Education	0.25	Years of schooling	Any household member has less than five years of schooling	0.125
		School attendance	School-age child not attending school	0.125
Income potential	0.25	Economic engagement	No household member engaged in any income-generating activity	0.125
		Transfers from outside the household	No external transfers received in the past 12 months	0.125
Living standards	0.25	Cooking fuel	Uses firewood, charcoal, dung or other unclean fuels	0.042
		Sanitation	No toilet facility or unsafe sharing ratio (more than 1:8)	0.042
		Electricity	No access to electricity	0.042
		Drinking water	No access to clean drinking water or travel time exceeds 30 minutes	0.042
		Housing material (roofing)	Roof made of grass thatch, sisal, palm or similar temporary materials	0.042
		Asset ownership	Owns one or fewer of: bicycle, mobile phone, car, television, radio, tractor, refrigerator	0.042

An individual or household is assigned a value of one if they experience deprivation in a specific indicator. The deprivation score is calculated by multiplying this value by the corresponding weight of the indicator. In a framework with 10 indicators, an individual deprived in all 10 would have a deprivation score of 1, while an individual experiencing no deprivation across any indicator would have a score of 0. The deprivation score is summarised as follows:

$$D_s = \sum_{i=1}^{i=n} w_i d_i, \tag{1}$$

in which
D_s is the deprivation score;
w_i is the weight associated with the indicator i; and
d_i is the deprivation of indicator i, taking on the value of 1 if the person is deprived, and 0 if otherwise.

2.3 Estimating the intensity of climate-smart agriculture

This study focuses on adoption intensity because smallholder farmers combine several practices to address multiple production constraints simultaneously. Combinations of complementary practices are expected to generate broader benefits by simultaneously improving productivity, reducing production risks, enhancing resource-use efficiency and strengthening resilience to climate variability (Matteoli *et al*. 2020).

Accordingly, adoption intensity is interpreted as the extent to which households integrate multiple CSA practices into their farming systems, rather than implying that every additional practice contributes equally or linearly to reducing multidimensional poverty. For this study, the count variable was converted into a binary treatment indicator to distinguish households with relatively high adoption intensity from those with low adoption intensity. Households adopting more than one CSA practice were classified as high-intensity/adopters (T = 1), while households adopting one or no CSA practice were classified as low-intensity/non-adopters (T = 0).

2.4 Estimation association of CSA adoption intensity and multidimensional poverty

The relationship between CSA adoption intensity and multidimensional poverty may be influenced by self-selection, as households adopting multiple CSA practices can differ systematically from others in both observed and unobserved characteristics. Ignoring these differences may bias the estimated association between CSA adoption intensity and multidimensional poverty.

To accurately evaluate this, a number of econometric approaches were considered. Instrumental variable (IV) models can address endogeneity when valid instruments are available, while difference-in-differences (DID) requires panel data with observations before and after treatment (Fentie & Beyene 2019; Asmare & Tabe-Ojong 2025; Mkupete 2025). Neither approach was appropriate for the present study. This is because the data is cross-sectional, making DID unfeasible, and a credible exclusion restriction that could strengthen the identification of the IV selection equation could not be established. Although frequency of extension visits has been used as an instrument in some previous studies, it is unlikely to satisfy the exclusion restriction in this study because extension services may influence household MPI through several channels other than CSA adoption, including improved farm management, access to information and productivity.

To account for this selection bias, the study employed endogenous switching regression (ESR) as the primary estimation approach. ESR jointly estimates the adoption decision and separate outcome equations for households with relatively high and low levels of CSA adoption. This framework accommodates differences in the relationship between household characteristics and MPI across the two groups, while accounting for both observed and unobserved factors associated with households' adoption decisions (Liu *et al*. 2021; Suresh *et al*. 2021; Zegeye *et al*. 2022).

The equations are presented as follows:

For adopters (T = 1):

$$MPI_1 = X\beta_1 + \varepsilon_1 \tag{5}$$

For non-adopters (T = 0)

$$MPI_0 = X\beta_0 + \varepsilon_0, \tag{6}$$

where MPI_1 and MPI_0 are multidimensional poverty indices for adopters and non-adopters, respectively,
X represents covariates influencing MPI,
β_1 and β_0 are parameters to be estimated, and
ε_1 and ε_0 are error terms capturing unobserved factors affecting MPI for adopters and non-adopters, respectively.

Since MPI_1 and MPI_0 cannot be observed simultaneously, the joint distribution of ε_1 and ε_0 cannot be identified directly. Assuming that $\rho_{0,1} = 1$, a simultaneous equations model with ESR is estimated using the full-information maximum likelihood (FIML) method. The estimated outcome equations are subsequently used to derive model-based predicted outcomes under the observed and alternative adoption regimes (Khonje *et al*. 2015). For adopters (T = 1), we estimate the observed MPI outcome for households with high CSA intensity as well as their counterfactuals, as shown below:

Actual: $$E(Y_1|T=1) = X\beta_1 \quad (7)$$

Counterfactuals $$E(Y_0|T=1) = X\beta_0 + \rho_{u,\epsilon_0\sigma_0\lambda(Z\gamma)} \quad (8)$$

Within the ESR framework, the average treatment effect on the treated (ATT) is reported as a model-based comparison between the observed and estimated counterfactual outcomes. Because the present study does not claim causal identification, ATT estimates should be interpreted as model-based associations rather than causal treatment effects. Thus, ATT is calculated as shown below

$$ATT = E(Y_1|T=1) - E(Y_0|T=1) \quad (9)$$

$$ATT = X\beta_1 - X\beta_0 - \rho_{u,\epsilon_0\sigma_0\lambda(Z\gamma)} \quad (10)$$

Similarly, for the non-adopters (T = 0), the actual, counterfactual and average treatment effect on untreated are estimated as follows:

Actual (T = 0) = $$E(Y_0|T=0) = X\beta_0 \quad (11)$$

Counterfactual = $$E(Y_1|T=0) = X\beta_1 + \rho_{u,\epsilon_1\sigma_1\lambda(-Z\gamma)} \quad (12)$$

$$ATU = E(Y_0|T=0) - E(Y_1|T=0) \quad (13)$$

$$ATU = X\beta_0 - X\beta_1 - \rho_{u,\epsilon_1\sigma_1\lambda(-Z\gamma)} \quad (14)$$

As a robustness check, Propensity Score Matching (PSM) was employed to assess whether the estimated associations were sensitive to the estimation approach. PSM balances households based on observed characteristics but does not account for unobserved heterogeneity.

3. Results and discussion

We proceed by presenting the descriptive Statistics, examining the estimates of the intensity of CSA adoption, and finally the distribution of CSA Practices among smallholder maize-farming households. The robustness test estimates are provided to validate the prior estimation approach. We also present some diagnostic test results to ascertain the validity of our estimates.

3.1 Descriptive statistics of households

Table 2 presents the descriptive statistics for the variables used in the analysis based on 8 091 maize-farming households. Household heads had an average age of 51.8 years, indicating a predominantly middle-aged farming population. Approximately 71% of households were male-headed (1 = male, 0 = female), while household heads had completed an average of 9.1 years of schooling. On average, households owned 2.8 productive assets, belonged to approximately three farmer or community groups, and 49.2% had access to credit.

CSA adoption intensity had a mean of 0.607, indicating that the adoption of multiple CSA practices remained relatively low among the sampled households. A detailed distribution of CSA adoption intensity is presented in the subsequent section.

The multidimensional poverty index (MPI) averaged 0.454, exceeding the national rural MPI reported by KNBS (2016). This suggests that maize-producing households experience relatively higher multidimensional deprivation than the average rural household. The average farm size was 0.89 acres, confirming the predominance of smallholder production systems. Average maize yield was 15.3 bags per acre. On average, households sold approximately five bags of maize with a wide variation in quantities sold, suggesting marked differences in commercialisation.

In addition, farmers received an average of 3.7 agricultural training sessions. Approximately 31.7% of households reported access to healthcare services.

Table 2: Descriptive statistics of variables used in estimations

Variable	Observations	Mean	Std. dev.	Min	Max
CSA-Intensity	8 091	0.607	0.698	0	3
Age of household head	8 091	51.849	13.488	20	100
Gender of household head	8 091	0.708	0.406	0	1
Marital status of household head	8 076	2.600	1.240	1	7
Years of schooling of household head	8 091	9.095	5.015	0	22
Assets (number)	8 091	2.779	1.097	0	7
Advice frequency (number)	8 091	3.711	13.962	0	260
Planting season	8 091	0.645	0.352	0	1
Farm size	8 091	0.889	0.814	0.01	5
Quantity sold	8 091	4.981	13.192	0	245
Sale price	2 704	2 753.273	3 059.344	10	6 000
Health access	8 091	0.317	0.465	0	1
Credit access	8 091	0.492	0.500	0	1
MPI	8 091	0.454	0.126	0.125	1
Group membership	8 091	3.056	2.190	1	12

Source: Authors' computation

Diagnostic tests included multicollinearity and heteroscedasticity assessments. Multicollinearity was examined using variance inflation factors (VIFs). As shown in Appendix 1, all VIF values were below 3 – below the acceptable threshold of 10 – indicating no multicollinearity concerns. Heteroscedasticity was tested using the Breusch–Pagan test, which yielded a chi-square statistic of 70.31 ($p < 0.001$), rejecting the null hypothesis of homoscedasticity. Consequently, all regression models were estimated using heteroscedasticity-robust standard errors (Appendix 2).

3.2 Intensity of adoption of climate smart agriculture

Table 3 presents the distribution of CSA adoption intensity. More than half of the sampled households (50.86%) had not adopted any of the selected CSA practices, while 38.39% had adopted one practice. Only 9.90% of households adopted two practices, and less than one percent (0.85%) had adopted three practices. The low prevalence of multiple-practice adoption may reflect the financial, technical and institutional constraints associated with implementing several climate-smart practices simultaneously (Kassa & Abdi 2022; Molua 2022; Ndung'u *et al*. 2023; Ma & Rahut 2024).

Table 3: Tabulation of CSA intensity

# of adopted strategies	Frequency	Percentage	Cumulative
0	4 115	50.86	50.86
1	3 106	38.39	89.25
2	801	9.90	99.15
3	69	0.85	100.00
Total	8 091	100.00	

Source: Authors' computation

3.3 Distribution of climate-smart agriculture (CSA) practices

Table 4 shows considerable variation in the adoption of individual CSA practices among smallholder maize-farming households. Integrated soil management recorded the highest adoption rate, of 18.68%, closely followed by integrated manure management at 17.98%. Agroforestry was adopted by 11.15% of households, whereas conservation agriculture and irrigation exhibited the lowest adoption rates, at 6.81% and 6.13% respectively. Overall, adoption rates for individual CSA practices remained relatively low, with more than four-fifths of households not adopting any specific practice.

Table 4: Adoption per CSA practice

CSA practice	Non-adopters, n (%)	Adopters, n (%)
Irrigation	7 595 (93.87)	496 (6.13)
Agroforestry	7 189 (88.85)	902 (11.15)
Integrated soil management	6 580 (81.32)	1 511 (18.68)
Integrated manure management	6 636 (82.02)	1 455 (17.98)
Conservation agriculture	7 540 (93.19)	551 (6.81)

3.4 Endogenous switching regression (ESR) results

To examine the association between CSA adoption intensity and MPI, the ESR model was estimated as shown in Table 5. This framework allows the relationship between household characteristics and MPI to differ across the two adoption regimes, while accounting for potential selection associated with households' adoption decisions.

Among non-adopting households, the age of the household head was negatively associated with MPI ($\beta = -0.0008$, $p < 0.01$). Older household heads experienced lower deprivation due to their accumulation of farming experience, production knowledge and asset ownership over time, which can improve household welfare (Kassa & Abdi 2022; Zegeye *et al*. 2022).

Education was also negatively associated with MPI among non-adopters ($\beta = -0.0040$, $p < 0.01$). Better-educated household heads were more likely to access agricultural information, understand improved farming practices and allocate household resources more efficiently, thereby reducing multidimensional deprivation. This is consistent with the work of Hasan *et al*. (2018), Ali *et al*. (2022) and Sanogo *et al*. (2023).

Membership of farmer groups exhibits a significant negative association with MPI for both adopters ($\beta = -0.0063$, $p < 0.01$) and non-adopters ($\beta = -0.0110$, $p < 0.01$). The larger coefficient among adopters suggests that social networks may strengthen the association between CSA adoption and household MPI by facilitating access to extension information, input markets, financial services and collective learning. Similar evidence has been reported by Mujeyi *et al*. (2021) and Ndung'u *et al*. (2023).

Table 5: Endogenous switching regression results

Variable	Non-Adopters	Adopters	Selection
HH Age	-0.0008***	-0.0006	0.0076***
	(0.0001)	(0.0004)	(0.0017)
HH Gender	-0.0030	-0.0124	-0.0796
	(0.0038)	(0.0123)	(0.0564)
HH Education	-0.0040***	-0.0008	0.0230***
	(0.0004)	(0.0011)	(0.0046)
Farm size	0.0011	-0.0069	0.0040
	(0.0019)	(0.0049)	(0.0250)
Planting season	-0.0032	-0.0059	0.0311
	(0.0046)	(0.0144)	(0.0696)
Credit access	0.0054	-0.0218	0.2048**
	(0.0085)	(0.0190)	(0.0987)
Group membership	-0.0063***	-0.0110***	0.0496***
	(0.0008)	(0.0021)	(0.0099)
Garissa	0.0390	-0.0391	-0.1846
	(0.0283)	(0.1161)	(0.4857)
Marsabit	0.0325***	0.0125	-0.2623**
	(0.0064)	(0.0254)	(0.1092)
Nyandarua	-0.0108*	0.0667**	-0.6044***
	(0.0062)	(0.0258)	(0.1018)
Nyeri	-0.0182***	-0.0332**	-0.0186
	(0.0051)	(0.0153)	(0.0749)
West Pokot	0.0759***	0.0149	-0.0149
	(0.0053)	(0.0168)	(0.0784)
Baringo	0.0239***	-0.0499***	0.4897***
	(0.0058)	(0.0139)	(0.0586)
Siaya	0.0174***	-0.0249	-0.2653***
	(0.0056)	(0.0205)	(0.0896)
Kisumu	0.03946	0.0413*	-0.3712***
	(0.0225)	(0.0229)	(0.0935)
Advice frequency (instrument)	—	—	0.0062***
	—	—	(0.0011)
Constant	0.5497***	0.6453***	-1.9855***
	(0.0106)	(0.0629)	(0.1506)

Source: Authors' computation

County-level coefficients reveal considerable spatial heterogeneity in MPI. Among non-adopters, households in Marsabit, West Pokot, Baringo and Siaya exhibited significantly higher MPI than the reference county, whereas households in Nyandarua and Nyeri exhibited significantly lower MPI. For adopters, MPI remained significantly higher in Nyandarua and Kisumu but significantly lower in Nyeri and Baringo. These differences may reflect variation in agroecological conditions, climate risks, infrastructure, market access and institutional support across counties.

The variance-covariance estimates presented in Table 6 provide evidence of non-random selection into the two CSA adoption regimes. The estimated standard deviations are relatively similar across the two regimes ($\sigma_0 = 0.132$; $\sigma_1 = 0.124$), indicating comparable variability in MPI outcomes. The estimated correlation coefficients are negative and statistically significant ($\rho_0 = -0.879$; $\rho_1 = -0.449$), indicating that unobserved household characteristics associated with CSA adoption are also associated with MPI, thus supporting the use of the ESR framework.

Table 6: Variance–covariance and selection correction parameters from the endogenous switching regression model

	Coef.	Std. error	z	P > z	[95% Confidence interval]	
/lns0	-2.021	0.012	-175.57	0	-2.044	-1.999
/lns1	-2.088	0.071	-29.45	0	-2.227	-1.949
/r0	-1.372	0.08	-17.21	0	-1.528	-1.216
/r1	-0.483	0.191	-2.53	0.011	-0.858	-0.109
sigma0	0.132	0.002			0.13	0.136
sigma1	0.124	0.009			0.108	0.142
rho0	-0.879	0.018			-0.91	-0.838
rho1	-0.449	0.153			-0.695	-0.108

Source: Authors' computation

Table 7 presents the ESR-derived counterfactual estimates for adopting and non-adopting households. These findings indicate that adopting households exhibited lower estimated MPI (-0.018) than their corresponding counterfactual outcomes. Likewise, non-adopting households exhibited higher MPI (0.026) relative to their estimated counterfactual outcomes. Although these estimates should not be interpreted as causal effects because a convincing exclusion restriction could not be established, they provide consistent evidence that higher CSA intensity is associated with lower MPI after accounting for observed household characteristics and potential selection associated with adoption decisions. Similar associations between CSA adoption and improved household welfare have been reported by Hasan *et al*. (2018), Ali *et al*. (2022) and Islam and Farjana (2024), although those studies employed different measures of household welfare.

Table 7: ATT and ATU for adopters and non-adopters

Group	MPI (observed)	MPI (counterfactual)	Difference	Std error	T-stat
Adopters (ATT)	0.438	0.456	-0.018	0.003	-2.31
Non-adopters (ATU)	0.458	0.432	0.026	0.004	3.44

Source: Authors' computation

3.5 Robustness check: Propensity score matching (PSM) results

PSM was employed to gauge the robustness of the ESR estimates. Unlike ESR, PSM estimates treatment effects by matching treated and untreated households with similar observed characteristics. Balance diagnostics showed substantial improvement in comparability after matching, with standardised mean differences declining and variance ratios approaching acceptable thresholds (Appendix 3), confirming that the matched sample was suitable for robustness analysis.

The PSM results are presented in Table 8. The matching procedure achieved substantial common support, with 7 570 observations retained within the region of common support and only four observations excluded. This indicates excellent overlap in the distribution of propensity scores between the treated and control groups, providing a reliable basis for estimating the ATT.

CSA-adopting households exhibited an MPI 0.006 points lower than comparable non-adopters. Although the estimate was smaller and statistically insignificant compared with the ESR model, the consistent negative direction supports the robustness of our finding that CSA adoption is associated with lower MPI.

Table 8: Treatment-effect estimation results

PSM	MPI (observed)	MPI (counterfactual)	Difference	Std error	T-stat	On support	Off support
Adopters (ATT)	0.438	0.444	-0.006	0.005	-1.3	7570	4

Source: Authors' computation

4. Summary and conclusion

This study examined the association between CSA adoption intensity and MPI among smallholder maize-farming households in Kenya using data from the KCSAP survey. CSA adoption intensity was measured as the number of CSA practices adopted by each household, and households were classified into high- and low-intensity adoption groups for the endogenous switching regression (ESR) analysis. Propensity score matching (PSM) was employed as a robustness check to assess whether the estimated associations were sensitive to the estimation approach.

The findings reveal that the adoption of multiple CSA practices remained relatively limited among maize-farming households. More than half of the sampled households had not adopted any of the selected CSA practices, while fewer than 1% had adopted three practices simultaneously. Among the individual practices considered, integrated soil management and integrated manure management recorded the highest adoption rates, whereas irrigation and conservation agriculture remained the least adopted.

The ESR results indicate that households with higher CSA adoption intensity are associated with lower MPI than households with lower adoption intensity. Household head age, education and membership of farmer groups were also associated with lower MPI, while substantial geographical differences were observed across counties. The significant selection parameters further indicate that households adopting higher levels of CSA differ systematically from those with lower adoption intensity, supporting the use of econometric approaches that account for potential selection.

The robustness analysis using PSM produced estimates that were consistent in direction with those obtained from the ESR model. Taken together, the findings suggest a stable negative association between higher CSA adoption intensity and MPI.

Based on the results of our findings, we propose some policy suggestions:

- *Promote integrated rather than single-practice CSA adoption*: Agricultural programmes implemented by the Ministry of Agriculture, county governments and development partners should promote complementary CSA technology packages instead of individual technologies. Extension programmes should demonstrate how practices such as integrated soil fertility management, manure management, agroforestry, conservation agriculture and irrigation can be combined to improve farm resilience and household MPI simultaneously.

- *Strengthen agricultural extension and farmer training:* Strengthening extension systems through increased staffing, continuous farmer training, demonstration farms, digital advisory platforms and climate information services would improve farmers' awareness of CSA technologies and enhance their capacity to implement multiple complementary practices.

- *Improve farmers' access to affordable financial services:* Policymakers should expand access to affordable agricultural credit, climate finance, input subsidy programmes and risk-sharing financial instruments that enable farmers to invest in CSA practices.

- *Strengthen farmer organisations and collective action:* Policies that support well-functioning farmer organisations should be promoted to enhance the dissemination and effective implementation of CSA technologies.

- *Design location-specific CSA interventions:* National and county governments should design location-specific CSA programmes that reflect local agroecological conditions, climate risks, infrastructure and market opportunities.

We acknowledge two limitations. First, the cross-sectional nature of the data limits the ability to capture changes in CSA adoption and MPI over time. The findings should therefore be interpreted as short-run treatment effects rather than long-term causal impacts. Second, CSA intensity was measured by the number of practices adopted, which may not reflect implementation quality. Nevertheless, the findings remain robust, context-specific, and relevant to similar African economies.

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References

Abhilash A, Rani A, Kumari A, Singh RN & Kumari K, 2021. Climate-smart agriculture: An integrated approach for attaining agricultural sustainability. In Chauhan AS, Rani A, Kumari A, Singh RN & Kumari K (eds.), Climate change and resilient food systems: Issues, challenges, and way forwards (pp. 141–89). Singapore: Springer. https://doi.org/10.1007/978-981-33-4538-6_5

Akpan AI & Zikos D, 2023. Rural agriculture and poverty trap: Can climate-smart innovations provide breakeven solutions to smallholder farmers? Environments 10(4): 57. https://doi.org/10.3390/ENVIRONMENTS10040057

Ali H, Menza M, Hagos F & Haileslassie A, 2022. Impact of climate-smart agriculture adoption on food security and multidimensional poverty of rural farm households in the Central Rift Valley of Ethiopia. Agriculture & Food Security 11: 62. https://doi.org/10.1186/S40066-022-00401-5

Alkire S & Foster J, 2011. Understandings and misunderstandings of multidimensional poverty measurement. Journal of Economic Inequality 9(2): 289–314. https://doi.org/10.1007/S10888-011-9181-4

Asante BO, Ma W, Prah S & Temoso O, 2024. Farmers' adoption of multiple climate-smart agricultural technologies in Ghana: Determinants and impacts on maize yields and net farm income. Mitigation and Adaptation Strategies for Global Change 29: 16. https://doi.org/10.1007/S11027-024-10114-8

Asmare F & Tabe-Ojong MP Jr, 2025. Climate-smart agriculture and climate resilience: Panel data evidence from Ethiopia. Climatic Change 178(11), 208. https://doi.org/10.1007/S10584-025-04053-9

Dushimiyimana C, Ngango J & Maniriho A, 2026. Climate change impacts on agricultural productivity and resilience in Sub-Saharan Africa. Discover Sustainability. https://doi.org/10.1007/s43621-026-03984-2

Erenstein O, Jaleta M, Sonder K, Mottaleb K & Prasanna BM, 2022. Global maize production, consumption and trade: Trends and R&D implications. Food Security 14(5): 1295–1319. https://doi.org/10.1007/S12571-022-01288-7

FAO, 2013. Building resilience for adaptation to climate change in the agriculture sector. Rome: Food and Agriculture Organization of the United Nations. https://www.fao.org/4/i3084e/i3084e00.htm

FAO, 2020. FAO policy on gender equality 2020–2030. Rome: Food and Agriculture Organization of the United Nations.
Fentie A & Beyene AD, 2019. Climate-smart agricultural practices and welfare of rural smallholders in Ethiopia: Does planting method matter? Land Use Policy 85, 387–96. https://doi.org/10.1016/j.landusepol.2019.04.020
Habtewold TM, 2021. Impact of climate-smart agricultural technology on multidimensional poverty in rural Ethiopia. Journal of Integrative Agriculture 20(4): 1021–41. https://doi.org/10.1016/S2095-3119(21)63637-7
Hasan MK, Desiere S, D'Haese M & Kumar L, 2018. Impact of climate-smart agriculture adoption on the food security of coastal farmers in Bangladesh. Food Security 10(4): 1073–88.
Hughes K, Morgan S, Baylis K, Oduol J, Smith-Dumont E, Vågen TG & Kegode H, 2020. Assessing the downstream socioeconomic impacts of agroforestry in Kenya. World Development 128: 104835. https://doi.org/10.1016/J.WORLDDEV.2019.104835
Ince-Palamutoğlu M, 2026. Food security in the face of climate change: Challenges and solutions. In Yenilmez MI & Altan MU (eds.), Green economics, finance and climate justice: Innovative solutions for a resilient and equitable world (pp. 109–20). Cham: Springer Nature Switzerland. https://doi.org/10.1007/978-3-032-17588-5_7
Islam MK & Farjana F, 2024. Impact of climate-smart agriculture practices on multidimensional poverty among coastal farmers in Bangladesh. Communications Earth and Environment 5: 417. https://doi.org/10.1038/S43247-024-01570-W
Jayne TS, Snapp S, Place F & Sitko N, 2019. Sustainable agricultural intensification in an era of rural transformation in Africa. Global Food Security 20: 105–13. https://doi.org/10.1016/J.GFS.2019.01.008
Kassa BA & Abdi AT, 2022. Factors influencing the adoption of climate-smart agricultural practice by small-scale farming households in Wondo Genet, Southern Ethiopia. SAGE Open 12(3). https://doi.org/10.1177/21582440221121604
Khonje M, Manda J, Alene AD & Kassie M, 2015. Analysis of adoption and impacts of improved maize varieties in Eastern Zambia. World Development 66, 695–706. https://doi.org/10.1016/J.WORLDDEV.2014.09.008
Kifle T, Ayal DY & Mulugeta M, 2022. Factors influencing farmers adoption of climate smart agriculture to respond climate variability in Siyadebrina Wayu District, central highland of Ethiopia. Climate Services 26: 100290. https://doi.org/10.1016/J.CLISER.2022.100290
KNBS, 2016. Basic report on well-Being in Kenya based on the 2015/16 Kenya integrated Household Budget survey (KiHBs). Nairobi, Kenya: Kenya National Bureau of Statistics.
Kogo BK, Kumar L & Koech R, 2021. Climate change and variability in Kenya: A review of impacts on agriculture and food security. Environment, Development and Sustainability 23(1): 23–43. https://doi.org/10.1007/S10668-020-00589-1
Lipper L, Thornton P, Campbell BM, Baedeker T, Braimoh A, Bwalya M, Caron P, Cattaneo A, Garrity D, Henry K, Hottle R, Jackson L *et al*., 2014. Climate-smart agriculture for food security. Nature Climate Change 4: 1068–72. https://doi.org/10.1038/nclimate2437
Liu M, Min S, Ma W & Liu T, 2021. The adoption and impact of E-commerce in rural China: Application of an endogenous switching regression model. Journal of Rural Studies 83: 106–16. https://doi.org/10.1016/J.JRURSTUD.2021.02.021
Ma W & Rahut DB, 2024. Climate-smart agriculture: Adoption, impacts, and implications for sustainable development. *Mitigation and Adaptation Strategies for Global Change* 29: 44. https://doi.org/10.1007/S11027-024-10139
Maguza-Tembo F, Abdi-Khalil E, Mangisoni J & Mkwambisi D, 2016. Does adoption of climate smart agriculture (CSA) technologies reduce household vulnerability to poverty? Journal of Economics and Sustainable Development 7(21): 125–30.

Matteoli F, Schnetzer J & Jacobs H, 2020. Climate-smart agriculture (CSA): An integrated approach for climate change management in the agriculture sector. In Leal Filho W, Luetz J & Ayal D (eds.), *Handbook of climate change management* (pp. 1–29). Cham: Springer. https://doi.org/10.1007/978-3-030-22759-3_148-1

Mkupete MJ, 2025. Is agricultural technology adoption effective in reducing multidimensional poverty? Panel data evidence from Tanzania. Food Policy 135: 102904. https://doi.org/10.1016/j.foodpol.2025.102904

Molua EL, 2012. Gendered response and risk-coping capacity to climate variability for sustained food security in Northern Cameroon. International Journal of Climate Change Strategies and Management 4(3): 277–307. https://doi.org/10.1108/17568691211248739

Molua EL, 2022. Private farmland autonomous adaptation to climate variability and change in Cameroon. Rural Society 31(2): 115-35. https://doi.org/10.1080/10371656.2022.2086223

Molua EL & Ayuk JE, 2021. Male–female sensitivity in climate-induced income insecurity: Some empirical evidence from farming households in Northern Cameroon. Development in Practice 31(8), 1014–39. https://doi.org/10.1080/09614524.2021.1937528

Molua EL, Benhin JKA, Kabubo-Mariara J, Ouedraogo M & El-Marsafawy S, 2010. Global climate change and vulnerability of African agriculture: Implications for resilience and sustained productive capacity. Quarterly Journal of International Agriculture 49(3): 183–211. https://doi.org/10.22004/AG.ECON.155547

Mucheru-Muna MW, Ada MA, Mugwe JN, Mairura FS, Mugi-Ngenga E, Zingore S & Mutegi JK, 2021. Socio-economic predictors, soil fertility knowledge domains and strategies for sustainable maize intensification in Embu County, Kenya. Heliyon 7(2): e06345. https://doi.org/10.1016/J.HELIYON.2021.E06345

Mujeyi A, Mudhara M & Mutenje M, 2021. The impact of climate smart agriculture on household welfare in smallholder integrated crop–livestock farming systems: Evidence from Zimbabwe. Agriculture and Food Security 10: 4. https://doi.org/10.1186/S40066-020-00277-3

Muriithi C, Mwongera C, Abera W, Chege CGK & Ouedraogo I, 2023. A scalable approach to improve CSA targeting practices among smallholder farmers. Heliyon 9(10), e20526. https://doi.org/10.1016/j.heliyon.2023.e20526

Ndung'u S, Ogema V, Thiga M & Wandahwa P, 2023. Factors influencing the adoption of climate smart agriculture practices among smallholder farmers in Kakamega County, Kenya. African Journal of Food, Agriculture, Nutrition and Development 23(10): 24759–82. https://doi.org/10.18697/ajfand.125.23400

Nyberg Y, Musee C, Wachiye E, Jonsson M, Wetterlind J & Öborn I, 2020. Effects of agroforestry and other sustainable practices in the Kenya Agricultural Carbon Project (KACP). Land 9(10): 389. https://doi.org/10.3390/LAND9100389

Okumu S, 2018. Impact of interventions by One Acre Fund on maize yield and farm profits in Busia County, Kenya. Master's thesis, Kenyatta University, Nairobi, Kenya. http://ir-library.ku.ac.ke/handle/123456789/19508

Priyadarshini P & Abhilash PC, 2020. Circular economy practices within energy and waste management sectors of India: A meta-analysis. Bioresource Technology 304: 123018. https://doi.org/10.1016/J.BIORTECH.2020.123018

Sanogo K, Touré I, Arinloye D-DAA, Dossou-Yovo ER & Bayala J, 2023. Factors affecting the adoption of climate-smart agriculture technologies in rice farming systems in Mali, West Africa. Smart Agricultural Technology 5: 100283. https://doi.org/10.1016/J.ATECH.2023.100283

Suresh K, Khanal U, Wilson C, Managi S, Quayle A & Santhirakumar S, 2021. An economic analysis of agricultural adaptation to climate change impacts in Sri Lanka: An endogenous switching regression analysis. Land Use Policy 109: 105601. https://doi.org/10.1016/J.LANDUSEPOL.2021.105601

Thornton PK, Whitbread A, Baedeker T, Cairns J, Claessens L, Baethgen W, Bunn C, Friedmann M, Giller KE, Herrero M, Howden M, Kilcline K *et al*., 2018. A framework for priority-setting in climate smart agriculture research. Agricultural Systems 167: 161–75. https://doi.org/10.1016/J.AGSY.2018.09.009

Tsegaye MH, 2020. Impacts of improved agricultural technologies adoption on multidimensional welfare indicators in rural Ethiopia. Doctoral dissertation, Addis Ababa University, Addis Ababa, Ethiopia. https://etd.aau.edu.et/server/api/core/bitstreams/8899efc4-9457-4a74-91cd-77819730de1a/content

World Bank, 2021. Kenya. Washington, DC: World Bank Group. https://www.worldbank.org/ext/en/country/kenya

Yitbarek E & Tesfaye W, 2022. Climate-smart agriculture, non-farm employment and welfare: Exploring impacts and options for scaling up. Sustainability 14(23): 15981. https://doi.org/10.3390/SU142315981

Zegeye MB, Meshesha GB & Shah MI, 2022. Measuring the poverty reduction effects of adopting agricultural technologies in rural Ethiopia: Findings from an endogenous switching regression approach. Heliyon 8(5): e09495. https://doi.org/10.1016/j.heliyon.2022.e09495

Zossou E, Arouna A, Diagne A & Agboh-Noameshie RA, 2020. Learning agriculture in rural areas: The drivers of knowledge acquisition and farming practices by rice farmers in West Africa. Journal of Agricultural Education and Extension 26(3): 291–306. https://doi.org/10.1080/1389224X.2019.1702066

Appendices

Appendix 1: Multicollinearity test results

	VIF	1/VIF
HH mstatus	2.177	.459
HH gender	2.16	.463
Yrs of schooling	1.149	.87
HH age	1.115	.897
CSA intensity	1.051	.951
Advice freq.	1.027	.974
Credit access	1.026	.975
Farm size	1.016	.985
Mean VIF	1.34	.

Source: Authors' computation

Appendix 2: Results of the propensity score matching test for balance

	Mean		t-test			V(T)/
Variable	Treated	Control	%bias	t	p > t	V(C)
HH age	52.944	52.872	.5	0.110	0.912	1.020
HH gender	1.146	1.117	7.6	1.740	0.081	1.200
HH mstatus	2.449	2.376	6.3	1.430	0.152	1.16
Advice freq.	7.824	6.345	6.6	1.040	0.298	1.17
Planting season	1.129	1.121	2.4	0.520	0.603	1.060
Farm size	0.943	1.065	-14.500	-2.660	0.008	0.80
Credit access	0.048	0.042	3.1	0.590	0.555	.

Source: Authors' computation

Appendix 3: Balance diagnostic Test Results

		Mean		% reduct		t-test	V(T)/	
Variable	**Matched/ unmatched**	**Treated**	**Control**	**%bias**	**bias**	**t**	**p > t**	**V(C)**
HH age	U	53.274	51.694	11.8	3.14	0.002	0.96	
	M	53.274	52.553	5.4	54.4	1.09	0.278	0.99
HH gender	U	1.152	1.216	-16.4	-4.19	0	0.76*	
	M	1.152	1.164	-3.1	81.2	-0.66	0.512	0.94
Years of schooling	U	10.429	8.939	30.2	8	0	0.93	
	M	10.429	9.869	11.4	62.4	2.32	0.02	1.01
Farm size	U	0.952	0.886	7.8	2.16	0.031	1.19*	
	M	0.952	0.909	5	35.2	1	0.318	1.14
Planting season	U	1.131	1.147	-4.6	-1.2	0.23	0.91	
	M	1.131	1.147	-4.5	1.1	-0.91	0.365	0.91
Credit access	U	0.056	0.031	12.1	3.68	0	.	
	M	0.056	0.043	6.5	46.6	1.23	0.22	.
Group membership	U	3.486	2.995	21.4	6.01	0	1.31*	
	M	3.486	3.109	16.4	23.1	3.22	0.001	1.23*
Garissa	U	0.001	0.003	-3.2	-0.76	0.445	.	
	M	0.001	0.002	-1.8	44.9	-0.39	0.697	.
Marsabit	U	0.031	0.067	-16.8	-3.99	0	.	
	M	0.031	0.05	-8.9	47	-1.95	0.051	.
Nyandarua	U	0.04	0.086	-19.4	-4.6	0	.	
	M	0.04	0.093	-22.1	-14.2	-4.34	0	.
Nyeri	U	0.171	0.135	10.1	2.81	0.005	.	
	M	0.171	0.144	7.6	24.2	1.51	0.131	.
West Pokot	U	0.09	0.111	-6.8	-1.77	0.076	.	
	M	0.09	0.094	-1.3	80.6	-0.28	0.782	.
Baringo	U	0.292	0.113	45.8	14.44	0	.	
	M	0.292	0.122	43.5	5.2	8.63	0	.
Siaya	U	0.055	0.088	-13	-3.23	0.001	.	
	M	0.055	0.088	-12.9	0.8	-2.6	0.009	.
Kisumu	U	0.046	0.089	-17.4	-4.21	0	.	
	M	0.046	0.09	-17.7	-1.6	-3.55	0	.

Source: Authors' computation