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Revisiting the Efficiency–Poverty Nexus: Evidence from Kenyan Smallholder Maize Farmers

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Abstract

The relationship between farm productivity and poverty reduction remains contested in settings characterised by persistent spatial inequality. This study examines whether technical efficiency is associated with multidimensional poverty among 8,434 smallholder maize farmers in Kenya, using Tegemeo Institute survey data collected under the Kenya Climate-Smart Agriculture Project during the 2020-2021 agricultural season across nine counties. Technical efficiency is estimated using a stochastic frontier approach while its effect on multidimensional poverty is analysed using an instrumental variable Tobit model with county fixed effects. Results indicate a mean technical efficiency level of 35.5 percent. In pooled specifications, technical efficiency is associated with lower multidimensional poverty; however, this relationship disappears once county-level heterogeneity is accounted for, suggesting that baseline results are driven by between-county variation rather than within-county differences. Further evidence from the first-stage analysis indicates that the identifying variation in the instrument is largely cross-county, implying weak within-county identification under fixed effects. Overall, multidimensional poverty is strongly shaped by spatial and structural county-level conditions, highlighting the importance of context-specific constraints in determining multidimensional poverty outcomes. The findings suggest that efficiency-enhancing interventions alone are insufficient for poverty reduction unless complemented by spatially targeted policies addressing infrastructure, market access, and institutional disparities.

KEYWORDS:
Technical efficiency; Multidimensional Poverty Index; Smallholder farmers; Kenya

1 | INTRODUCTION

Farm productivity is widely regarded as a key pathway to poverty reduction in smallholder agriculture. However, evidence on whether improvements in technical efficiency translate into reductions in multidimensional poverty remains inconsistent. The inconsistency is heightened in settings characterized by pronounced spatial and structural inequalities. This study investigates whether technical efficiency is associated with reduced multidimensional poverty among smallholder maize farmers in Kenya and whether this relationship is robust to spatial heterogeneity.

A substantial body of literature using stochastic frontier analysis documents significant inefficiencies among smallholder farmers, indicating persistent gaps between observed and potential output (Belete, 2020; Bibi et al., 2021; Birhanu et al., 2021;

Mwangi et al., 2020). However, these studies mostly focus on yield or income effects with limited attention to broader welfare outcomes such as health, education, and living standards captured by the multidimensional poverty index. As a result, the extent to which efficiency gains translate into improvements in overall well-being remains insufficiently understood.

Technical inefficiency arises from a combination of managerial, institutional, and structural constraints, including limited access to information, credit, and markets, as well as environmental variability. These factors prevent farmers from achieving maximum output from available resources and contribute to persistent productivity gaps in smallholder agriculture (Geffersa & Agbola, 2025; Haryanto et al., 2023; Ruzhani & Mushunje, 2025).

In the Kenyan context, smallholder maize farmers exhibit substantial variation in technical efficiency reflecting differences in managerial ability, access to inputs, information, and institutional support. Empirical evidence suggests that technical efficiency levels range from as low as 8 percent to about 60 percent (Kibaara & Kavoi, 2012; Mutoko, 2008; Olwande & Smale, 2014). This indicates considerable scope for productivity improvement. At the same time, structural constraints such as market access, infrastructure, and agro-ecological conditions shape both production possibilities and multidimensional poverty outcomes.

This study is motivated by a key empirical observation: the association between technical efficiency and multidimensional poverty is not stable once spatial heterogeneity is accounted for. In pooled specifications, higher technical efficiency is associated with lower multidimensional poverty but this relationship disappears when county-level fixed effects are introduced. This suggests that the observed TE-MPI relationship is largely driven by between-county structural differences rather than within-county efficiency variation.

Based on this motivation, the study addresses three research questions: (i) What is the level of technical efficiency among smallholder maize farmers in Kenya? (ii) Does technical efficiency reduce multidimensional poverty in pooled and spatially controlled models? and (iii) Does the TE-MPI relationship persist after accounting for county-level heterogeneity and endogeneity? The study contributes to the literature in three ways: first, it links farm-level technical efficiency to multidimensional poverty rather than income alone; second, it explicitly tests the stability of the TE-MPI relationship under county fixed effects; and third, it demonstrates that spatial heterogeneity is central to understanding the efficiency–poverty nexus in Kenya.

2 | LITERATURE REVIEW

2.1 | Theoretical Literature Review

This study is grounded in an integrated theoretical framework linking production theory, efficiency measurement, human capabilities, institutional and spatial constraints. Together, these perspectives explain how farm-level production decisions translate into multidimensional poverty outcomes and why spatial heterogeneity may condition the relationship between technical efficiency and multidimensional poverty.

The theory of production provides the starting point for understanding agricultural output decisions. It conceptualizes production as a process in which inputs such as land, labor, capital, and intermediate inputs are transformed into output. Within this framework, the production frontier represents the maximum feasible output achievable with a given set of inputs under existing technology. Farmers operating below this frontier are considered technically inefficient because they fail to fully utilize available resources (Wongnaa and Awunyo-Vitor, 2018; Chepng'etich et al., 2015; Bibi et al., 2021). In smallholder agriculture, deviations from the frontier arise due to differences in managerial ability, input allocation decisions, and access to productive resources. This theoretical foundation motivates the measurement of technical efficiency as a core indicator of farm performance.

Stochastic frontier analysis (SFA) developed by Aigner et al. (1977) provides the empirical framework for operationalizing this concept. Unlike deterministic production functions, SFA decomposes deviations from the frontier into two components: random noise and inefficiency. Random noise captures factors beyond the farmer's control such as weather shocks, pests, and measurement error, while inefficiency reflects controllable factors such as poor management or suboptimal input use. This decomposition is relevant in agriculture where production is highly stochastic. In this study, SFA provides the basis for estimating technical efficiency and linking it to multidimensional poverty outcomes.

However, agricultural efficiency alone does not fully explain the differences in multidimensional poverty across households. The capability approach developed by Sen (1999) broadens the analysis by defining poverty as the failure to achieve basic functionings such as good health, education, and adequate living standards. From this perspective, multidimensional poverty reflects multiple overlapping deprivations rather than a single monetary metric (Alkire et al., 2016). Within this framework, improvements in technical efficiency may enhance household capabilities through higher income, improved food security, and better access to services. However, the translation from efficiency gains to capability expansion is not automatic and may depend on structural and contextual conditions.

Institutional and human capital theories help explain this conditionality. Human capital theory argues that education, skills, and knowledge enhance decision-making and productivity (Schultz, 1961). In agriculture, farmers with higher levels of education and training can allocate inputs efficiently, adopt improved technologies, and respond to production risks thereby increasing technical efficiency (Hoang-Khac et al., 2022). Institutions further shape these outcomes by determining access to markets, credit, extension services, and infrastructure. Weak institutional environments can constrain both efficiency and welfare outcomes by limiting farmers' ability to optimize production and convert output gains into improved living standards (Pathak et al., 2025; Ruzhani and Mushunje, 2025; Birhanu et al., 2021). Thus, both human capital and institutions operate as key mediating factors in the efficiency-welfare nexus.

Importantly, institutional conditions are often spatially heterogeneous meaning that households operating in different geographic regions face systematically different constraints and opportunities. Variations in agro-ecological conditions, infrastructure development, and market integration imply that the relationship between technical efficiency and multidimensional poverty may differ across counties. This provides the theoretical justification for incorporating county-level fixed effects in empirical estimation. By controlling for these structural differences, the analysis isolates within-county variation in efficiency and more accurately assesses its independent contribution to multidimensional poverty.

2.2 | Empirical Literature Review

Globally, smallholder maize production has expanded due to improvements in agricultural technology, input use, and agronomic practices. However, increases in output do not necessarily translate into uniform improvements in technical efficiency (TE). Across the literature, TE estimates vary widely reflecting differences in methodology, agro-ecological conditions, institutional environments, and sampling frameworks rather than purely differences in farmer performance. For instance, while the global average TE is estimated at approximately 72 percent (Ruzhani & Mushunje, 2025), studies in developed economies such as the European Union and China report higher efficiency levels ranging between 82 and 97 percent (Bibi et al., 2021; Radlińska, 2023; Wu et al., 2022). These higher values are largely attributed to advanced production technologies, stronger institutions, and better functioning input and output markets. They are also influenced by methodological choices such as functional form and estimation technique.

In contrast, lower TE levels are consistently reported in developing economies where inefficiency is more pronounced due to structural and institutional constraints. For example, Pathak et al. (2025) report an average TE of 28.7 percent among smallholder farmers in Nepal while estimates in Sub-Saharan Africa range from 24 to 83 percent (Ateka et al., 2018; Birhanu et al., 2021; Geffersa and Agbola, 2025; Kiprop et al., 2015; Mwangi et al., 2020; Tumuri et al., 2024). This wide dispersion suggests that inefficiency is not solely a reflection of farmer ability but is also shaped by differences in production environments, input market access, and econometric specification. Within Kenya, similar heterogeneity is observed with TE estimates ranging from 24 to 70 percent across studies (Alulu et al., 2021; Kamau et al., 2020; Kamau et al., 2017; Kiprop et al., 2015; Mwangi et al., 2020). This variation highlights the importance of spatial and institutional context in explaining efficiency outcomes.

The determinants of technical efficiency identified in the literature can be broadly grouped into five categories: farmer-specific characteristics, farm-level characteristics, institutional and market factors, environmental conditions, and socioeconomic household factors. However, these determinants do not operate independently. They interact within broader structural and institutional environments. Farmer-specific characteristics such as education level, farming experience, age, contact with agricultural extension officers, and access to training influence how well a farmer understands input combinations, planting schedules, pest control, and overall farm planning (Ateka et al., 2018; Chepng'etich et al., 2015; Kamau et al., 2020; Mwangi et al., 2020). However, their effect is often conditional on access to complementary resources such as credit and inputs, indicating that human capital alone is insufficient to guarantee efficiency gains.

Farm-level characteristics such as farm size, land fragmentation, soil fertility, irrigation access, mechanization, and technology adoption also play a critical role. Larger and more consolidated plots reduce coordination costs and improve supervision. Access to irrigation reduces yield variability and improves input responsiveness. Conversely, degraded soils, poor infrastructure, and fragmented landholdings increase operational inefficiencies and push farmers further from the production frontier (Ateka et al., 2018; Kamau et al., 2020; Kiprop et al., 2015; Omondi et al., 2020; Ruzhani and Mushunje, 2025). These structural constraints indicate that inefficiency may be embedded within production systems rather than purely attributable to farmer behavior.

Institutional and market factors further mediate efficiency outcomes. Access to credit, functioning input and output markets, storage facilities, and transport infrastructure influence the ability of farmers to allocate resources optimally. Credit constraints result in suboptimal input bundles even when farmers possess adequate technical knowledge. High transaction costs and price volatility create uncertainty, which can in turn encourage risk-averse behavior that leads to conservative input use and lower realized efficiency. Institutional arrangements such as cooperatives and government programs can mitigate these constraints; however, their effectiveness varies across contexts (Chepng'etich et al., 2015; Haryanto et al., 2023; Kamau et al., 2020; Ruzhani and Mushunje, 2025).

Environmental and agro-climatic conditions introduce additional complexity. Rainfall variability, temperature shocks, pest infestations, and soil degradation affect input productivity and increase production risk (Deshmukh et al., 2023). Under high climatic uncertainty, farmers may deliberately underutilize inputs to minimize potential losses resulting in observed inefficiency relative to the stochastic frontier. Persistent adverse conditions can thus create structural inefficiency that is beyond the immediate control of farmers.

As with technical efficiency, multidimensional poverty (MPI) remains unevenly distributed across regions. In Sub-Saharan Africa, MPI ranges between 26 percent and 66 percent (Birhanu et al., 2021; Danso-Abbeam, 2025; Habtewold, 2021; Islam & Farjana, 2024; Qaim and Ogutu, 2018) while in Kenya, it is estimated at approximately 36 percent (Qaim & Ogutu, 2018). This variation reflects differences in income, health, education, and access to basic services across regions.

Key determinants of multidimensional poverty include the gender of the household head, crop diversification, age, farm size, household size, group membership, health status, and marital status (Danso-Abbeam, 2025; Islam and Farjana, 2024). However, these determinants do not operate independently but are influenced by productivity and efficiency levels within agricultural systems.

Empirical studies examining the relationship between technical efficiency and poverty suggest a generally inverse relationship. Obayelu et al. (2022) found dynamic poverty transitions linked to efficiency outcomes among rural farmers, while Radlińska (2023) observed that higher crop productivity was associated with lower MPI scores. Similarly, Birhanu et al. (2021) reported that a 10 percent increase in technical efficiency reduced multidimensional poverty by 15.3 percent. These findings indicate that efficiency improvements enhance welfare through increased income and improved access to essential services. Despite this evidence, most studies do not explicitly account for spatial heterogeneity in estimating this relationship, particularly within sub-national contexts.

In addition, although existing studies separately examine technical efficiency and multidimensional poverty, key gaps still remain. First, the literature documents substantial variation in TE across regions, but does not systematically explain whether this variation arises from methodological differences, agro-ecological conditions, or institutional contexts. Second, while determinants of TE are well studied, fewer studies integrate the interaction of structural, institutional, and environmental constraints in a unified framework. Third, although evidence suggests that efficiency improvements reduce multidimensional poverty, limited empirical work explicitly links technical efficiency to multidimensional poverty while accounting for spatial heterogeneity within countries.

This study addresses these gaps by examining the relationship between technical efficiency and multidimensional poverty among smallholder maize farmers in Kenya, explicitly incorporating county-level heterogeneity using an instrumental variable Tobit framework. By doing so, it contributes to the literature by providing a spatially sensitive understanding of how productivity translates into welfare outcomes in structurally diverse agricultural systems.

3 | METHODOLOGY

3.1 | Data and Data Sources

The analysis draws on household-level data compiled by the Tegemeo Institute of Agricultural Policy and Development in partnership with the Ministry of Agriculture, Livestock, Fisheries, and Cooperatives under the Kenya Climate-Smart Agriculture Project. The dataset originates from the 2020–2021 survey round and focuses on maize-producing households. In total, 8,434 respondents were covered, drawn from nine counties namely Marsabit, Garissa, Nyandarua, Nyeri, West Pokot, Uasin Gishu, Baringo, Siaya, and Kisumu.

The cross-sectional dataset contains four major dimensions: health, living standards, economic participation, and education. These dimensions capture relevant information used to measure the multi-dimensional poverty index and household resilience. The dataset also contains additional information relating to maize production. The Stratified random sampling was adopted to ensure a representative and balanced sample. The preliminary step was the selection of nine counties forming the major strata for geographical representation. In each stratum, households were further classified into two groups: those who received an input subsidy and those who did not. Households were then randomly sampled from each sub-stratum for inclusion in the study. This multi-stage sampling approach guaranteed heterogeneity and a fairly representative sample, minimizing selection bias and increasing the validity and generalizability of the research findings.

Sampling weights provided were not applied in the estimation because the analysis focuses on modelling structural relationships rather than producing population-representative descriptive statistics. Consistent with applied econometric practice, the estimations are conducted in an unweighted form to preserve efficiency and avoid potential distortions in parameter estimates that may arise from weighting. Robust standard errors are used to account for potential heteroskedasticity in the estimations.

3.2 | Measuring Multidimensional Poverty

This study operationalizes household welfare using a multidimensional poverty framework that extends beyond conventional consumption-based measures to capture deprivations across key functionings and resilience domains. Consistent with the Alkire-Foster approach, poverty is conceptualized as a condition arising from simultaneous deprivations in multiple dimensions of well-being rather than a single monetary threshold (Alkire & Foster, 2011).

However, given the agrarian and climate-sensitive context of smallholder farming systems in Kenya, the standard global MPI specification is adapted to incorporate an additional financial resilience dimension. This extension is motivated by evidence that in rural developing-country contexts, vulnerability is not only reflected in deprivation of basic services but also in limited capacity to absorb shocks and smooth consumption during periods of income volatility. The income potential dimension is therefore designed to capture households' access to external financial support and informal risk-sharing mechanisms that enhance their ability to withstand adverse shocks (Barrett & Constas, 2014).

Within this framework, reliance on external transfers is interpreted as an indicator of constrained internal resilience and weak shock-absorbing capacity rather than a simple measure of consumption supplementation. The receipt of external transfers may also reflect heightened economic distress or strong social networks and support systems while the absence of such transfers may similarly indicate either self-reliance or limited access to informal safety nets. In structurally vulnerable rural economies, the absence of such external support channels is therefore associated with heightened exposure to welfare instability, complementing standard deprivation indicators.

The aggregation strategy assigns equal weights across the four dimensions to maintain transparency, comparability, and methodological simplicity, consistent with common practice in multidimensional poverty measurement (Bonareri, 2018). While this approach avoids subjective prioritization of welfare domains, it is acknowledged that equal weighting may imply differential effective contributions of individual indicators within the composite index depending on the dimensional structure.

To ensure that empirical findings are not driven by the choice of aggregation scheme, robustness checks are conducted using the standard three-dimensional global MPI structure. The consistency of results across these alternative constructions confirms that the main findings are not sensitive to the weighting scheme or dimensional extension adopted in this study. The specific dimensions, indicators, and weights are presented in Table 1.

TABLE 1 The domesticated structure of the National MPI

Dimension	Weight	Indicator	Deprivation cut-off	Weight
Health	0.25	Nutrition	Household skipped at least one meal / reported inadequate nutrition	0.125
		Access to healthcare	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

Source: Authors' compilations borrowing from Alkire et al., 2011 framework

A household is assigned a value of one if it experiences deprivation in a specific indicator. The deprivation score is then calculated by multiplying this value by the corresponding weight of the indicator. In a framework with ten indicators, a household deprived of all ten would have a deprivation score of 1, while a household experiencing no deprivation across any indicator would have a score of 0. The deprivation score is summarized 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.

d_i is the deprivation of indicator i, taking on the value of 1 if the household is deprived, and zero if otherwise.

3.3 | Estimating Technical Efficiency

Several approaches exist for estimating technical efficiency. Deterministic frontier models and Data Envelopment Analysis (DEA) were not adopted because they attribute all deviations from the frontier to inefficiency, ignoring stochastic shocks such as weather variability, pests, and measurement error which are important in smallholder agriculture. In addition, DEA is highly sensitive to outliers and does not allow statistical inference. A one-step stochastic frontier inefficiency model was also not used due to its restrictive distributional assumptions linking inefficiency determinants directly to the frontier (Ndirangu et al.2018).

Given these limitations, the study adopted the standard Stochastic Frontier Analysis (SFA) framework following Aigner et. al. (1977). SFA is preferred because it decomposes deviations from the production frontier into inefficiency and random noise, making it well-suited to agricultural production systems characterized by uncertainty.

3.4 | Determinants of Technical Efficiency

Technical efficiency scores are bounded between 0 and 1 limiting the suitability of conventional linear models such as ordinary least squares which can generate predictions outside this range. Alternative approaches such as GMM and truncated regression are also inappropriate due to their assumptions regarding functional form, censoring, or unbounded outcomes. Tobit models were considered but are only appropriate for censored data rather than naturally bounded fractional variables (Burton, 2021; Rahman and Dilanchiev, 2021).

Given these limitations, the study employs a fractional logit model designed for proportion data and accommodates boundary values at 0 and 1. The model ensures predicted values remain within the unit interval and is estimated using quasi-maximum likelihood thus producing consistent and robust estimates of the determinants of technical efficiency (Ahmed et al., 2017). The fractional logit model is as shown:

$$Y_i = G(X_i\beta) \tag{2}$$

Where
Y_i is the dependent variable
G(.) is the logistic function
X_i is a vector of explanatory variables
β is a vector of coefficients to be estimated
The fractional logit model is estimated using the Quasi-maximum likelihood (QMLE) as shown;

$$L(\beta) = \sum_{i=1}^{n}[Y_i \ln G(X_i\beta) + (1 - Y_i)\ln(1 - G(X_i\beta))] \tag{3}$$

3.5 | Technical Efficiency and Household Poverty Among Smallholder Maize Farmers in Kenya

As discussed by Birhanu et al. (2021), technical efficiency and household poverty are related. This is grounded in the hypothesis that more efficient households tend to achieve higher incomes and experience better overall welfare outcomes. Similarly, farmers with lower MPI have a higher tendency to employ new technologies on their farms leading to higher efficiency. Due to a possible reverse causal relationship between the two variables, potential endogeneity may impact the estimated parameter. Therefore, the study adopted an Instrumental Variable (IV) to handle the reverse causality problem as implemented by Birhanu et al. (2021).

The literature identifies various potential instruments that can be used. These include distance to markets, distance to the extension office, access to market information, land quality, land tenure, number of oxen, distance to an input source, and availability of fertilizer subsidy (Battese & Coelli, 1995; Birhanu et al., 2021; Kumbhakar & Lovell, 2012; Mason & Jayne, 2012). The selected instrument must satisfy the two conditions cited by Wooldridge (2012): it must exhibit a strong association with the endogenous independent variable (technical efficiency) while remaining uncorrelated with the regression error term.

The instrument selected for this study was access to market information due to data availability and its ability to satisfy instrument validity conditions. However, access to market information may influence multidimensional poverty through channels other than production efficiency, such as improved price negotiation, market participation, income diversification, and access to non-farm opportunities. To address this concern, the study conducted a plausibly exogenous bounds analysis as developed by Conley et al. (2012). This relaxes the strict exclusion restriction by allowing the instrument to exert a small direct effect on the multidimensional poverty index.

To test the hypothesis that TE has no impact on MPI, the study employed the instrumental variables (IV) Tobit model. This model is appropriate given that the dependent variable, MPI, is censored and assumes non-negative values with a potential point mass concentration at zero (Birhanu et al., 2021). Additionally, the possibility of reverse causality suggests the presence of endogeneity which the IV approach addresses effectively. This improves the reliability of the estimated relationship between technical efficiency and multidimensional poverty. The instrumental variable Tobit model is of the form:

$$Y^* = \beta_0 + \beta_1 T_i + \beta_2 X_i + \mu_i \tag{4}$$

The observed values of the dependent values takes on the form;

$$Y_i = 0 \text{ if } Y^* \leq 0, \quad Y^* \text{ if } Y^* > 0 \tag{5}$$

Where

Y^* is the unobserved values of the dependent variable (MPI) which can be positive or negative

T_i is the endogeneous variable

X_i are other covariates influencing the outcome of the dependent variable

Y_i is the observed values of the dependent variable.

3.6 | Analytical Model for Stochastic Frontier Analysis

To estimate the technical efficiency for each household, the study adopted the Cobb-Douglas production form due to its ability to handle correlation, multicollinearity, and heteroscedasticity (Mitra and Yunus, 2018). The analytical model as shown:

$$\ln y_i = \beta_0 + \beta_1 \ln x_1 + \beta_2 \ln x_2 + \beta_3 \ln x_3 + \beta_4 \ln x_4 + \beta_5 \ln x_5 + v_i - u_i \tag{6}$$

Where,

x_{1i} represent the seed quantity used by household i in kilograms per acre

x_{2i} represent labour used by household i in Ksh per acre

x_{3i} represent herbicides used by household i in Litres per acre

x_{4i} represent the quantity of fertilizer used by household i in Kilograms per acre

x_{5i} represent farm size under maize farming by household i in acres

Technical efficiency is then estimated as;

$$TE_i = \frac{Y_i}{Y_{Max}} = e^{-\mu} \tag{7}$$

Where Y_i represents the maize output for household i and Y_{Max} is the maximum possible output.

3.7 | Analytical Model for the Fractional Logit Model

To estimate the determinants of technical efficiency, a fractional logit model was used as implemented by Ahmed et al. (2017) and Aminou (2021). The model is as shown;

$$TE_i = \alpha_0 + \alpha_1 x_{1i} + \alpha_2 x_{2i} + \cdots + \alpha_7 x_{7i} + \varepsilon_i \tag{8}$$

Where,

TE_i represent the technical efficiency of household i which is in form of fraction between 0 and 1

$x_{1i} \cdots x_{7i}$ represent the covariates, for example, age of the household head, gender, group membership, years of schooling of the household head, frequency of extension services, and access to credit for household i. $\alpha_0 \cdots \alpha_7$ are the parameters to be estimated. ε_i is the error term.

3.8 | Analytical model for the Instrumental Variable Tobit Model

To evaluate the effect of technical efficiency on multidimensional poverty among the smallholder maize farmers in Kenya, the instrumental variable Tobit model was used as implemented by Birhanu et al. (2021). The model is as shown;

$$MPI_i = \beta_0 + \beta_1 TE_i + \beta_k X_{ki} + \lambda_1 D_{1i} + \cdots \lambda_8 D_{8i} + \varepsilon_i \tag{9}$$

Where

MPI_i is household i MPI score.

TE_i is technical efficiency score for household i

X_{ki} confounding factors such as age of the household head, gender, group membership, years of schooling of the household head, frequency of extension services, and access to credit for household i.

$D_1 \cdots \cdots \cdots D_8$ are dummy variables for the 8 counties, except Uasin Gishu county, which acts as the reference county.

$\beta_0 \cdots \beta_k$ and $\lambda_1 \cdots \lambda_8$ are parameters to be estimated, and

ε_i is the error term assumed to be homoscedastic, normally distributed, with zero mean.

4 | RESULTS AND DISCUSSIONS

4.1 | Diagnostic Test Results

To test access to market information for instrument relevance, a two-step instrumental variable regression was estimated to obtain the instrument F-statistic. The instrument F-statistic was 13.4121 with a corresponding p-value of 0.0003 confirming the relevance of using access to market information as an instrument for technical efficiency. To test for endogeneity of the instrument, the Durbin-Wu-Hausman test was conducted. The results show a robust chi-square score of 58.751 and a corresponding p-value of 0.000, indicating that technical efficiency is endogenous. Therefore, the use of an instrumental variable approach was justified.

VIFs for the variables of interest were estimated to assess whether the variables are correlated with each other. All the VIFs are below 10, confirming that no multicollinearity problem exists.

The Breusch-Pagan test was employed to test for homoscedasticity. The chi-square statistic was found to be 66.81 with a p-value of 0.0000, indicating the presence of non-constant variance. To address this issue, robust standard errors were utilized to adjust for heteroscedasticity.

The Shapiro-Wilk Test was performed to assess whether the residuals followed a normal distribution. The results indicate that the residuals from the first-stage regression deviate from normality ($W = 0.84492$, $p < 0.001$). However, given the large sample size and the use of robust standard errors in the IV Tobit model, the estimates are reliable for inference.

4.2 | Stochastic Frontier Model

To estimate the household technical efficiency scores, stochastic frontier analysis was conducted. All variables are specified in logarithmic form. Maize output is measured as the total harvested quantity in kilograms at the household level. Farm size refers to the cultivated maize area in acres rather than total land owned. Labour is measured as total hired and family labour expenditure (KSh) per acre, while fertilizer, seed, and herbicide are measured as physical quantities applied per acre. This specification implies that land represents cultivated production scale, while other inputs capture the intensity of use per unit of land. The results are presented in Table 2.

TABLE 2 Stochastic Frontier (normal/half-normal) Results

ln_Y	Coef.	St.Err.	t-value	p-value	[95% Conf.	Interval]
ln Farm Size	.959***	0.010	93.7	0.000	0.939	0.979
ln_labor_cost	.076***	0.019	4.03	0.000	0.039	0.114
ln_seed qty	-0.128	0.339	-0.38	0.706	-0.792	0.536
ln_herbicide cost	-0.058	0.059	-0.99	0.324	-0.174	0.058
ln fertilizer qty	.067***	0.008	8.15	0.000	0.051	0.083
Constant	3.055***	0.865	3.53	0.000	1.359	4.752
-						
Constant	2.042***	0.086	-23.67	0.000	-2.211	-1.873
Constant	1.162***	0.024	47.66	0.000	1.114	1.210
/lnsig2v	-2.042	0.086	-23.67	0.000	-2.211	-1.873
/lnsig2u	1.162	0.024	47.66	0.000	1.114	1.210
sigma_v	0.360	0.016			0.331	0.392
sigma_u	1.788	0.022			1.746	1.831
sigma2	3.327	0.071			3.187	3.466
Lambda	4.962	0.034			4.896	5.029

*** p<.01, ** p<.05, * p<.1
Source: Authors' computations

The estimates show that farm size, labour cost, and fertilizer quantity have a significantly positive effect on maize output whereas seed quantity and herbicide cost have no statistical significance. The elasticity of farm size is 0.959, implying that a 1 percent increase in farm size leads to approximately a 0.96 percent increase in output holding other factors constant. This suggests that cultivated maize area acts as the primary scale determinant of output in smallholder systems where expansion of land under maize directly translates into higher production. However, this magnitude should be interpreted with caution given that other production inputs are specified as intensity variables. This specification may mechanically amplify the relative importance of land in the production structure.

To assess the robustness of this result, a translog stochastic frontier model was estimated to relax the assumption of constant input elasticities and allow for nonlinearities and interaction effects among inputs as shown in Appendix 1. The results indicate that the marginal effect of land is non-linear and less precisely estimated under the flexible specification. This reflects substantial interaction among production inputs and multicollinearity in higher-order terms. While the translog form suggests that land is an important input in smallholder maize production, the estimated land elasticity of 5.08 implies that this model does not yield a stable or statistically precise estimate. This suggests that the additional flexibility may have introduced estimation noise without materially improving interpretability. Overall, the evidence indicates that although the Cobb–Douglas specification is restrictive, it provides a more stable and interpretable characterization of production technology in this context and the conclusion regarding the central role of land remains broadly supported.

Labour cost has an elasticity of 0.076, indicating that a 1 percent increase in labour expenditure raises output by 0.076 percent. Similarly, fertilizer quantity has an elasticity of 0.067, implying that a 1 percent increase in fertilizer use increases maize output by 0.067 percent, consistent with the findings of Mwangi et al. (2020).

The sum of the estimated elasticities is 0.916, implying decreasing returns to scale. This means that a proportional increase in all inputs results in a less-than proportional increase in output. If all the inputs are increased by 1 percent, output increases by 0.92 percent. This finding suggests that production is operating within Stage II of the production function (the rational zone) but with evidence of scale inefficiency. The significant variance parameter (1.162) further confirms the presence of technical inefficiency thereby justifying the use of stochastic frontier analysis instead of conventional ordinary least squares estimation.

The estimated standard deviation of random noise (σ_v) is 0.360. This random component captures factors beyond the farmer's control such as weather variability, measurement errors, and other external shocks. In contrast, the standard deviation of inefficiency (σ_u) is 1.788, which is substantially larger than σ_v. Since $\sigma_u > \sigma_v$ and $\lambda = 4.962 > 1$, it means that inefficiency effects dominate random noise. This provides strong support for the stochastic frontier framework. The computed gamma (γ)

was 0.960, indicating that 96 percent of the total variation in output is attributable to technical inefficiency, while only 4 percent is explained by random shocks.

Gamma was computed as follows:

$$\gamma = \frac{\delta_u^2}{\delta_u^2 + \delta_v^2}\gamma = \frac{1.787937^2}{0.3603126^2 + 1.787937^2} = 0.96097296 \tag{10}$$

4.3 | Levels of Technical Efficiency by Gender

TABLE 3 Technical efficiency by gender

Household head gender	Mean	SD	Min	Max
Female	0.331	0.239	0.010	0.888
Male	0.361	0.258	0.003	0.953
Total	0.355	0.255	0.003	0.953

Source: Authors' computations

The results show that maize farmers operate at about 35.5 percent of their potential output. This indicates that there is substantial scope to increase output by approximately 64.5 percent if inefficiencies are addressed. The results conform to those of Mwangi et al. (2020), who found an average TE of 39.55 percent among tomato farmers in Kirinyaga County with household efficiency levels ranging from 3.6 percent to 94.6 percent. Results further show modest differences in technical efficiency between male- and female-headed households. Male-headed households recorded a slightly higher mean technical efficiency score of 0.361 compared to female-headed households which recorded 0.331. This suggests that on average, male-headed households operate closer to the production frontier than their female counterparts. However, the difference in mean efficiency is relatively small (0.03), indicating that the performance gap is not large in magnitude.

4.4 | Robustness and Sensitivity of Technical Efficiency Estimates

The robustness of technical efficiency estimates is assessed across alternative stochastic frontier specifications by varying both functional form and distributional assumptions. The analysis focuses on three dimensions of stability: level stability, rank stability, and structural consistency of efficiency scores.

Level stability is evaluated by comparing mean efficiency scores across models. The results show that while the exponential specification yields higher mean efficiency, the Cobb-Douglas, truncated-normal, and translog models produce closely aligned estimates, ranging between approximately 0.298 and 0.365. This indicates limited sensitivity of efficiency levels to model specification, with the exception of the exponential case, which compresses inefficiency dispersion.

Rank stability is assessed using Spearman correlation coefficients across efficiency estimates. The results reveal near-perfect rank consistency with correlations exceeding 0.98 across all model pairings and reaching 0.999 between the Cobb–Douglas and truncated-normal specifications. This indicates that the ordering of farmers by technical efficiency is invariant to both functional form and distributional assumptions.

The half-normal specification in this study is retained as the baseline model because it is standard and most widely accepted in stochastic frontier analysis, consistent with the seminal formulation of stochastic frontier models in Aigner et.al (1977). It provides stable and reliable estimates under the production technology considered in this study. In contrast, although the exponential specification yields higher mean efficiency estimates, it is treated as a sensitivity case because it imposes a different distributional structure on inefficiency that tends to compress the inefficiency term and inflate efficiency levels. Importantly, the ranking of farmers remains highly consistent across all specifications, indicating that the main inference is driven by the underlying production structure rather than the choice of inefficiency distribution. The results were summarized in Table 4.

TABLE 4 Robustness and Sensitivity Results of Technical Efficiency Estimates

Model	Distribution	Mean TE	Std Dev	Min	Max	Spearman ρ (vs baseline)
Cobb–Douglas	Half-normal	0.355	0.255	0.003	0.953	1.000
Cobb–Douglas	Truncated-normal	0.298	0.237	0.002	0.966	0.999
Cobb–Douglas	Exponential	0.778	0.047	0.370	0.881	0.984
Translog	Half-normal	0.365	0.25	0.003	0.948	0.992

Source: Authors' computations

4.5 | Fractional logit model to evaluate determinants of Technical Efficiency

Table 5 presents fractional logit estimates showing the conditional associations between household characteristics and technical efficiency. The estimates should be interpreted as conditional associations rather than causal determinants given the potential for simultaneity and reverse causality between productivity outcomes and household characteristics such as schooling years, credit access, and group membership.

TABLE 5 Fractional Logit Regression Results

Robust TE	Coef.	Std.Err.	z	P>z	[95%Conf. Interval]	
Farm Size	-0.016	0.016	-1.010	0.313	-0.048	0.015
HH Age	-0.004***	0.001	-3.830	0.000	-0.005	-0.002
HH Gender	-0.104***	0.031	-3.360	0.001	-0.164	-0.043
Yrs of Schooling	0.018***	0.003	7.230	0.000	0.013	0.023
Advice Freq.	0.000	0.001	0.270	0.784	-0.001	0.002
Credit Access	0.002	0.070	0.030	0.976	-0.135	0.139
Group Member	-0.050***	0.006	-8.210	0.000	-0.061	-0.038
_cons	-0.229***	0.070	-4.120	0.000	-0.428	-0.152

*** p<.01, ** p<.05, * p<.1
Source: Authors' computations

The results indicate that age, gender, group membership, and years of schooling of the household head are significantly associated with technical efficiency, while the effects of farm size, frequency of advice, and credit access were not.

The age of the household head had a significant negative association with TE ($\beta = -0.004$, $p < 0.01$). This implies that as the household head grows a year older, technical efficiency declines by 0.004 units holding other factors constant. This finding reflects reduced physical capacity, slower adaptation to improved technologies, and lower responsiveness to new production methods among older farmers as cited by Ateka et al. (2018) and Tumuri et al. (2024).

The gender of the household head was also significantly associated with TE ($\beta = -0.104$, $p < 0.05$). As the gender of the household head moves from male to female, the level of technical efficiency declines by 0.104 points. This suggests that female-headed households have on average lower technical efficiency compared to the reference category (male). The result points to possible differences in management approaches, resource utilization, or decision-making dynamics across gender categories that influence efficiency outcomes (Boudalia et al., 2024; Omondi et al., 2020).

Group membership was also significantly associated with technical efficiency ($\beta = -0.050$, $p < 0.01$). The results indicate that farmers who participate in groups tend to exhibit lower levels of technical efficiency compared to non-members. This may reflect time reallocation and coordination costs associated with group participation where farmers devote productive farm time to meetings, training sessions, and other group obligations. In addition, multiple group memberships may dilute managerial attention and labour supervision capacity as farmer groups in rural settings are primarily welfare or finance-oriented rather than productivity-enhancing.

In addition, years of schooling of the household head had a significant positive association with TE ($\beta = 0.018$, p < 0.01). An additional year of schooling increases efficiency by 0.018 units holding other factors constant. Education enhances managerial skills, information processing capacity, and the ability to adopt improved farming practices, thereby increasing productive efficiency (Ateka et al., 2018).

4.6 | Instrumental Variable Tobit Model

To evaluate the poverty-reducing effect of technical efficiency, a baseline instrumental variable regression model was estimated. The results are presented in Table 6.

TABLE 6 Baseline IV Tobit Results for the effect of TE on MPI

MPI	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]
TE	-1.102***	0.322	-3.430	0.001	-1.733	-0.472
HH Age	-0.002***	0.000	-6.420	0.000	-0.003	-0.002
HH Gender	-0.027***	0.009	-2.810	0.005	-0.045	-0.008
Schooling Yrs	-0.002	0.001	-1.430	0.154	-0.005	0.001
Advice Freq.	0.000	0.000	-0.410	0.681	-0.001	0.000
Credit Access	-0.007	0.019	-0.340	0.733	-0.044	0.031
Constant	1.024***	0.125	8.160	0.000	0.778	1.270
corr(e.TE,e.MPI)	0.918	0.042			0.783	0.971
sd(e.MPI)	0.304	0.075			0.188	0.493
sd(e.TE)	0.254	0.001			0.251	0.256
Mean dependent var	0.355	SD dependent var		0.256		
Number of obs	8434	Chi-square		113.131		
Prob > chi2	0	Akaike crit. (AIC)		10935.9		

*** p<.01, ** p<.05, * p<.1
Source: Authors' computations

The Instrumental Variable (IV) Tobit results provide strong evidence that technical efficiency (TE) significantly reduces multidimensional poverty among smallholder farmers. A one-unit increase in TE leads to a 1.102-unit decline in the latent MPI score, holding other factors constant. Considering that the mean MPI is 0.355, this magnitude suggests that efficiency improvements are economically meaningful in lowering deprivation levels. This result confirms the findings that improved efficiency enhances output without increasing input use, thereby raising farm income and improving household welfare outcomes such as education, health, and living standards (Obayelu et al., 2022).

The age of the household head has a significant negative effect on MPI (coef. = -0.0020, p < 0.001). This suggests that older household heads experience slightly lower levels of multidimensional poverty. Although the magnitude appears small, its statistical significance indicates a systematic effect. The result may reflect accumulated farming experience, better resource management skills, or stronger asset accumulation over time, all of which contribute to reduced deprivation.

Household head gender is also statistically significant ($\beta = -0.0270$, p = 0.005). The negative coefficient implies that male-headed households have a latent Multidimensional Poverty Index that is 0.027 points lower than that of female-headed households. This finding may reflect structural inequalities in access to productive resources, land ownership, credit markets, and extension services, which disproportionately disadvantage female-headed households. The result highlights the importance of gender-sensitive agricultural and poverty reduction policies.

4.7 | IV Tobit Model with County-specific Fixed Effects

TABLE 7 IV Tobit model on poverty reducing effects of Technical Efficiency with County Fixed Effects

MPI	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]
TE	-2.667	2.560	-1.040	0.297	-7.684	2.350
HH Age	-0.002	0.001	-1.630	0.103	-0.005	0.000
HH Gender	-0.034	0.034	-1.000	0.316	-0.100	0.032
Schooling Yrs	0.001	0.005	0.170	0.861	-0.010	0.012
Advice Freq.	0.000	0.000	0.470	0.639	-0.001	0.001
Credit Access	-0.052	0.060	-0.860	0.389	-0.171	0.066
County						
Garissa	-0.273	0.320	-0.850	0.393	-0.899	0.354
Marsabit	-0.456	0.457	-1.000	0.319	-1.351	0.440
Nyandarua	-0.367	0.328	-1.120	0.263	-1.102	0.276
Nyeri	-0.391	0.349	-1.120	0.262	-1.074	0.292
West Pokot	-0.282	0.350	-0.810	0.420	-0.967	0.403
Baringo	-0.266	0.260	-1.030	0.305	-0.775	0.243
Siaya	-0.607	0.588	-1.030	0.302	-1.760	0.546
Kisumu	-0.560	0.542	-1.030	0.302	-1.622	0.503
Constant	1.824	1.233	1.480	0.139	-0.592	4.241
corr(e.TE,e.MPI)	0.984	0.030			0.507	1.000
sd(e.MPI)	0.655	0.609			0.106	4.045
sd(e.TE)	0.242	0.001			0.239	0.244
Mean dependent var	0.355	SD dependent var		0.256		
Number of obs	8434	Chi-square		45.533		
Prob > chi2	0.000	Akaike crit. (AIC)		12190.591		

*** p<.01, ** p<.05, * p<.1
Source: Authors' computations

This specification extends the baseline IV Tobit model by incorporating county-specific fixed effects to control for unobserved time-invariant heterogeneity at the county level that may simultaneously influence technical efficiency and multidimensional poverty. By accounting for structural county characteristics such as agro-ecological conditions, infrastructure quality, market access, and institutional capacity, the model isolates the within-county effect of technical efficiency on multidimensional poverty. The model remains jointly significant (Chi-square = 45.533, $p < 0.001$) indicating that the regressors collectively explain variation in MPI. Unlike the baseline model with ρ=0.918 (CI: 0.783-0.971), when county effects are introduced, the estimate increases to $\rho = 0.984$, with the confidence interval extending close to unity. This suggests that controlling for county-level heterogeneity reduces the portion of variation attributed to statistical noise, thereby attributing a larger share of the residual variation to inefficiency. Although the county-augmented specification yields a value of ρ close to the boundary, the baseline model confirms that inefficiency is already substantial and statistically well identified.

The coefficient on TE is negative (β= -2.667), consistent with theoretical expectations and prior studies arguing that improvements in technical efficiency reduce multidimensional poverty (Birhanu et al., 2021; Job & Oladeebo, 2012). However, the estimate is no longer statistically significant (p = 0.297). This contrasts with the baseline model, where TE exhibited a strong and significant poverty-reducing effect. To further assess instrument validity under the fixed effects specification, a first-stage regression including county fixed effects was estimated. The results in Appendix 3 indicate that access to market information was no longer statistically significant once county fixed effects are introduced ($\beta = 0.0059$, p = 0.290), suggesting that much of the explanatory variation in the instrument operates across counties rather than within counties. Therefore, the results suggest that the within-county effect of technical efficiency on multidimensional poverty is weakly identified once county-level heterogeneity is absorbed.

The substantial increase in the standard error of TE (2.560) further indicates reduced precision in the fixed-effects specification. This likely reflects the absorption of cross-county variation by county fixed effects, thereby restricting identification to limited within-county variation in the data. As a result, the precision of the TE coefficient is reduced in line with the weak within-county identifying variation discussed in the first-stage results(Liu et al., 2023). The results imply that the efficiency-poverty relationship observed in the baseline model largely reflects structural geographic disparities rather than purely household-level efficiency differentials.

Overall, the findings indicate that county-level structural conditions play a central role in explaining the household multidimensional poverty index. While improvements in technical efficiency are expected to reduce deprivation, their poverty-reducing effect appears contingent upon the broader structural environment in which households operate as discussed by Betancourt et al. (2024). These results suggest that policies aimed solely at improving farm-level efficiency may be insufficient for sustained multidimensional poverty reduction unless complemented by interventions that address structural county-level constraints including infrastructure development, institutional strengthening, and market integration.

In addition, concerns remain regarding the validity of the exclusion restriction underlying the instrumental variable strategy. In practice, access to market information may influence multidimensional poverty through channels other than technical efficiency, such as improved market participation, income diversification, and price realization. To formally assess the sensitivity of the IV estimates to potential violations of this assumption, a plausibly exogenous bounds analysis following Conley et al. (2012) is implemented within a specification that controls for county-level fixed effects and the results presented in Appendix 2. The results indicate that the estimated effect of technical efficiency on multidimensional poverty is highly sensitive to moderate relaxations of the exclusion restriction. Although the coefficient on technical efficiency remains negative, it is statistically insignificant ($p = 0.912$) and the confidence interval is extremely wide (-50.09948 to 44.76801). This implies that once both structural heterogeneity and potential violations of instrument exogeneity are considered, the causal effect of technical efficiency on multidimensional poverty cannot be precisely identified.

To establish the robustness of the results, an IV Tobit model with county fixed effects using the three global MPI dimensions was estimated. Similar to the four-dimensional MPI model used in this study, the coefficient on technical efficiency remains negative as shown in Table 8. This suggests that improvements in technical efficiency are associated with reductions in multidimensional poverty. Although the coefficient is statistically insignificant in both specifications, the direction and magnitude remain relatively stable, suggesting that the relationship is not sensitive to the choice of MPI construction.

Similarly, the estimated correlation between the error terms remains high across the two models (ρ=0.984 in the four-dimensional specification and ρ=0.974 in the three-dimensional specification) indicating strong endogeneity and justifying the use of the endogenous Tobit framework. The county effects also remain broadly stable across the two specifications. Counties such as Siaya, Kisumu, Marsabit, and Nyeri consistently exhibit relatively larger negative coefficients relative to the reference category, suggesting persistent spatial heterogeneity in multidimensional poverty outcomes regardless of the MPI definition employed.

TABLE 8 Robustness of the Technical Efficiency–MPI Relationship Under Alternative MPI Specifications

Variables	4-Dimension National MPI	3-Dimensional Global MPI
TE	-2.667	-2.106
	(2.560)	(2.042)
HH Age	-0.002	-0.002**
	(0.001)	(0.001)
HH Gender	-0.034	-0.028
	(0.034)	(0.027)
Schooling Years	0.001	-0.003
	(0.005)	(0.004)
Advice Frequency	0.000	0.000
	(0.000)	(0.000)
Credit Access	-0.052	-0.047
	(0.060)	(0.048)
Garissa	-0.273	-0.157
	(0.320)	(0.256)
Marsabit	-0.456	-0.318
	(0.457)	(0.364)
Nyandarua	-0.367	-0.254
	(0.328)	(0.262)
Nyeri	-0.391	-0.304
	(0.349)	(0.278)
West Pokot	-0.282	-0.180
	(0.350)	(0.279)
Baringo	-0.266	-0.178
	(0.260)	(0.207)
Siaya	-0.607	-0.448
	(0.588)	(0.469)
Kisumu	-0.560	-0.407
	(0.542)	(0.433)
Constant	1.824	1.515
	(1.233)	(0.983)
corr(e.TE,e.MPI) / ρ	0.984	0.974
sd(e.MPI)	0.655	0.521
sd(e.TE)	0.242	0.242
Observations	8,434	8,434
Wald χ^2	45.533	124.64
Prob > χ^2	0.000	0.000

Source: Authors' computations

4.8 | Sensitivity Analysis Using Leave-One-County-Out (LOCO) Approach

To further test the robustness of the results, a leave-one-county-out (LOCO) sensitivity analysis was conducted to examine whether the estimated effect of technical efficiency on multidimensional poverty is driven by any specific county. The results were reported in Table 9.

TABLE 9 Leave-One-County-Out Sensitivity Analysis

Excluded County	TE coefficient	Robust st. error	P-value
None (Table 7 output)	-2.667	2.560	0.297
Garissa	-2.979	3.116	0.339
Marsabit	-2.263	2.167	0.296
Nyandarua	-2.733	2.873	0.341
Nyeri	-1.214	0.736	0.099
West Pokot	-3.685	5.883	0.531
Uasin Gishu	-3.584	4.090	0.381
Baringo	-4.283	4.468	0.338
Siaya	-1.569	0.980	0.109
Kisumu	-10.490	6.880	0.127

Source: Authors' computations

The coefficient on technical efficiency remains consistently negative across all subsamples, confirming that the direction of the relationship is stable. In addition, the estimates are largely statistically insignificant with marginal significance observed when Nyeri county is excluded. This pattern suggests that the earlier loss of statistical significance after controlling for county-level fixed effects is not due to the influence of any single county. Instead, it reflects broader structural and spatial differences across regions. Overall, the LOCO results indicate that the relationship between technical efficiency and multidimensional poverty is shaped by underlying geographic conditions and is not sensitive to the exclusion of individual counties.

5 | CONCLUSIONS AND POLICY SUGGESTIONS

The analysis of smallholder maize farmers in Kenya reveals that technical efficiency significantly determines maize output and indirectly influences multidimensional poverty. The stochastic frontier results indicate that farm size, labor expenditure, and fertilizer use positively increase maize output while seed and herbicide inputs are not statistically significant. Technical efficiency levels are low, averaging 35.5 percent, indicating substantial room for improvement. Gender differences are modest, with male-headed households being more efficient than female-headed counterparts. This reflects small but notable disparities in resource management and production practices. The fractional logit results further show that household head age, gender, and years of schooling significantly influence efficiency, suggesting that human capital and management skills are critical for realizing production potential.

The poverty-reducing effect of technical efficiency is highly dependent on spatial context. In the baseline IV Tobit specification, higher technical efficiency was associated with significantly lower multidimensional poverty. However, once county-specific fixed effects were introduced, the relationship became statistically insignificant. The leave-one-county-out sensitivity analysis further confirmed that this result was not driven by any single county.

These findings suggest that the relationship between technical efficiency and multidimensional poverty in Kenya is largely explained by between-county structural differences rather than within-county efficiency variation alone. Counties with higher average technical efficiency levels may also possess broader structural advantages, including better infrastructure, stronger market integration, more favorable agro-ecological conditions, and improved institutional support systems. Consequently, the poverty-reducing effect of technical efficiency observed in pooled models partly reflects underlying geographic and structural inequalities. The plausibly exogenous bounds analysis further showed that the estimated effect of technical efficiency is sensitive to moderate violations of the exclusion restriction after controlling for county fixed effects. In addition, the first-stage fixed effects specification indicated weak within-county explanatory power of the instrument, suggesting limited within-county identifying variation once county heterogeneity is absorbed. Therefore, the fixed effects results suggest reduced identification precision rather than definitive evidence that technical efficiency has no welfare effect within counties.

Overall, the study demonstrates that improving farm-level efficiency alone may be insufficient for sustained reductions in multidimensional poverty reduction among smallholder farmers. Policies aimed at reducing rural poverty should therefore move beyond productivity-enhancing interventions and simultaneously address broader county-level structural constraints. The following policy suggestions are based on the findings;

1. Integrate Efficiency Programs with County-Level Infrastructure and Market Development

Policies promoting technical efficiency such as improved seed provision, fertilizer optimization, and agronomic training should be combined with investments in rural infrastructure, market access, and storage facilities to ensure that productivity gains translate into measurable reductions in poverty. For example, in Siaya and Homa Bay counties where smallholder farmers often face high post-harvest losses and long distances to markets, county governments could establish ward-level aggregation centres equipped with drying facilities and structured buyer contracts through cooperatives. This would ensure that gains in productivity translate into actual income and poverty reduction rather than being lost through market inefficiencies.

2. Promote Education and Capacity Building for Farmers

Since age, gender, and years of schooling of the household head significantly affect technical efficiency, programs that enhance literacy, provide training in modern farming techniques, and gender-sensitive capacity-building can improve farm-level performance and reduce efficiency gaps between male and female-headed households. County agricultural offices could implement practical farm schools delivered through demonstration plots and digital advisory, using text message platforms in local languages, focusing on input calibration, weather-based planting decisions, and record-keeping for farm planning. In addition, counties can include women-focused extension quotas, bundled input credit schemes delivered through women's savings groups, and simplified mobile-based input financing systems that do not require collateral-heavy formal banking access.

3. Design Spatially Targeted Interventions

County-specific structural differences play a key role in shaping MPI outcomes. Policymakers should implement tailored interventions in underperforming counties focusing on institutional support, climate-resilient agriculture, access to affordable credit, and extension services to complement farm-level efficiency improvements. For example, the arid counties of Garissa, Marsabit, and West Pokot could design "County Productivity and Poverty Reduction Packages" such as packages that combine irrigation expansion along viable river basins, subsidized drought-resilient seed distribution, mobile veterinary and agronomic extension units, and public works programs linking infrastructure development to income support. This integrated approach directly addresses both inefficiency and deprivation simultaneously, consistent with the strong county-level effects identified in the model.

6 | LIMITATIONS OF THE STUDY

This study has several limitations that should be acknowledged when interpreting the findings. First, the analysis is based on cross-sectional data which limits the ability to establish causal dynamics over time or examine how changes in technical efficiency influence multidimensional poverty trajectories across periods. Second, the instrumental variable approach relies on a single instrument, and although diagnostic tests support its validity and relevance, the use of one instrument restricts the possibility of conducting additional overidentification tests.

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Conflicts of Interest

The authors report that there are no competing interests to declare.

Data Availability Statement

The data used in this study were obtained from the Tegemeo Institute of Agricultural Policy and Development. The dataset is not publicly available due to data access restrictions and ownership policies of the Institute. Access to the data can be granted upon reasonable request and with formal approval from the Tegemeo Institute of Agricultural Policy and Development.

Appendix 1: Translog stochastic frontier model Results

Variables	Coef.	Std. Err.	z	p-value	Lower CI	Upper CI
ln_farm_size	-0.997	2.572	-0.39	0.698	-6.039	4.045
ln_labor_cost	0.504	1.828	0.28	0.783	-3.079	4.087
ln_seedqty	0.348	6.255	0.06	0.956	-11.912	12.609
ln_herbicide_cost	-0.246	0.832	-0.30	0.768	-1.876	1.385
ln fertilizer qty	1.043	0.819	1.27	0.203	-0.562	2.647
ln farm size^2	0.080***	0.009	9.08	0.000	0.063	0.098
ln_labor_cost^2	-0.047***	0.007	-6.54	0.000	-0.061	-0.033
ln_seedqty^2	-0.049	0.187	-0.26	0.795	-0.415	0.318
ln_herbicide_cost^2	0.019	0.056	0.34	0.736	-0.090	0.128
ln_fertilizer_qty^2	0.021***	0.004	5.10	0.000	0.013	0.029
ln_farm_labor	0.006	0.018	0.35	0.723	-0.028	0.041
ln_farm_seed	-0.017	1.134	-0.01	0.988	-2.239	2.206
ln_farm_herb	0.257***	0.097	2.65	0.008	0.067	0.447
ln_farm_fert	0.018*	0.010	1.84	0.066	-0.001	0.037
ln_labor_seed	-0.038	0.797	-0.05	0.962	-1.601	1.524
ln_labor_herb	0.048	0.077	0.63	0.530	-0.102	0.199
ln_labor_fert	-0.019	0.020	-0.95	0.340	-0.059	0.020
ln_seed_herb	Omitted					
ln_seed_fert	Omitted					
ln_herb_fert	-0.126	0.108	-1.17	0.242	-0.337	0.085
Constant	-0.059	14.080	-0.00	0.997	-27.656	27.537

Source: Authors' computations

Appendix 2: Conley et al. (2012) LTZ Sensitivity Analysis Results

Variable	Coef.	Std. Error	z	P>|z|	[95% Conf.	Interval]
TE	-2.666	24.201	-0.11	0.912	-50.099	44.768
HH Age	-0.002	0.012	-0.19	0.849	-0.025	0.021
HH Gender	-0.034	0.274	-0.12	0.901	-0.570	0.502
Yrs of Schooling	0.001	0.049	0.02	0.984	-0.095	0.097
Advice Frequency	0.000	0.001	0.30	0.765	-0.001	0.002
Credit Access	-0.052	0.365	-0.14	0.886	-0.767	0.662
Garissa	0.287	2.395	0.12	0.905	-4.407	4.980
Marsabit	0.104	0.843	0.12	0.902	-1.549	1.756
Nyandarua	0.192	2.060	0.09	0.926	-3.845	4.230
Nyeri	0.168	1.836	0.09	0.927	-3.431	3.767
West Pokot	0.278	1.872	0.15	0.882	-3.391	3.946
Baringo	0.559	5.112	0.11	0.913	-9.460	10.578
Siaya	0.293	2.702	0.11	0.914	-5.002	5.588
Kisumu	-0.047	0.442	-0.11	0.914	-0.913	0.818
Constant (_cons)	1.264	6.293	0.20	0.841	-11.070	13.599

Source: Authors' computations

Appendix 3: First Stage Regression with County Fixed Effects

Variable	Coef.	Std. Err.	t-value	p-value	Lower CI	Upper CI
Market Info Access	0.006	0.006	1.06	0.290	-0.005	0.0168
HH Age	-0.001	0.000	-2.39	0.017	-0.0009	-0.0001
HH Gender	-0.011	0.007	-1.73	0.084	-0.0241	0.0015
Schooling Yrs	0.002	0.001	3.51	0.000	0.0009	0.0032
Advice Frequency	0.000	0.000	-0.13	0.894	-0.0004	0.0003
Credit Access	-0.015	0.016	-0.92	0.355	-0.0466	0.0167
Garissa	-0.112	0.051	-2.22	0.026	-0.2115	-0.0133
Marsabit	-0.176	0.011	-15.73	0.000	-0.1984	-0.1544
Nyandarua	-0.126	0.011	-11.37	0.000	-0.1478	-0.1044
Nyeri	-0.135	0.008	-16.08	0.000	-0.1518	-0.1188
West Pokot	-0.134	0.009	-14.32	0.000	-0.1522	-0.1155
Baringo	-0.100	0.010	-9.81	0.000	-0.1195	-0.0797
Siaya	-0.229	0.009	-25.46	0.000	-0.2471	-0.2117
Kisumu	-0.211	0.009	-22.86	0.000	-0.2293	-0.1931
Constant	0.471	0.019	24.94	0.000	0.4341	0.5082

Source: Authors' computations

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