Boosting Productivity: The Impact of Improved Sesame Varieties on Small-Scale Farmers in Mtwara, Tanzania

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Abstract

This study examines the adoption patterns of sesame varieties among small-scale farmers in the Mtwara region of Tanzania and analyzes the effects of adopting improved varieties on productivity the study Utilizing a non-experimental cross-sectional research design, the study collects data from a sample of 150 farmers using simple random sampling to ensure representativeness. The research area, Nanyumbu, Mtwara was chosen due to its significance in sesame production, diverse agro-climatic conditions, and substantial small-scale farming community. Data is gathered through primary sources and analyzed using the Endogenous Switching Regression (ESR) model to address self-selection bias. The research reveals that 67.13% of farmers continue to use local sesame varieties, while 27.9% utilize a combination of improved and local varieties, and 13.33% have fully adopted improved sesame varieties. The study identifies significant factors influencing adoption and productivity, including access to credit, market connectivity, and land ownership for adopters, and age, marital status, education level, and access to agricultural inputs for non-adopters. The analysis demonstrates that adopters of improved varieties experience a substantial increase in productivity, with a mean difference of 37.94 bags per acre compared to non-adopters. These findings underscore the role of financial access and market connections in enhancing agricultural outcomes and provide valuable insights for improving sesame production practices in the region.

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1. Introduction

Improving productivity is a key driver of economic growth and prosperity globally (Kitole, 2023; Vasanthan *et al.,* 2019; Kitole *et al.,* 2024). In Africa, enhanced productivity is recognized as crucial for sustainable development and poverty reduction (Tibamanya *et al.,* 2022). Similarly, in Tanzania, productivity plays a vital role in fostering economic progress and improving livelihoods (Kafando, 2023).

Despite its importance, small-scale farmers worldwide face numerous challenges in achieving higher productivity. These challenges include limited access to resources, inadequate infrastructure, and technological constraints (Teklu *et al.*, 2021). In Africa, additional challenges such as land degradation, climate variability, and limited market access further hinder productivity. In Tanzania, specific barriers include limited access to agricultural inputs such as improved seed varieties, poor extension services, and inadequate irrigation infrastructure (Wacal *et al.,* 2021).

Globally, efforts to boost productivity among small-scale farmers have focused on investment in agricultural research and development, promoting sustainable agricultural practices, and improving access to credit and markets (Myint *et al.,* 2020). In Africa, initiatives such as capacity-building, technology transfer programs, and rural infrastructure investment have been prioritized (ILO, 2020; Utouh & Kitole, 2024). In Tanzania, strategies to improve productivity include the implementation of poverty reduction initiatives, agricultural diversification, and the introduction of improved crop varieties like sesame (Tibamanya *et al.,* 2022).

However, despite these efforts, many households in Tanzania continue to struggle with low productivity. Understanding the drivers of improved sesame varieties adoption and their impact on productivity is essential to addressing these challenges. While several studies have examined the determinants of adoption of improved sesame varieties (e.g., Vasanthan *et al.,* 2019; Myint *et al.,* 2020; Kitole *et al.,* 2023; Teklu et al., 2021; Wacal *et al.,* 2021; Kitole & Sesabo, 2022; Kafando, 2023), few have specifically explored the socio-economic factors influencing adoption in Mtwara Region, Tanzania. This study aims to fill this knowledge gap by assessing the impact of adopting improved sesame varieties on productivity among small-scale farmers in Mtwara.

Sesame productivity is particularly important in Tanzania, as it drives economic growth for farmers, improves livelihoods, and helps reduce poverty (Nadu *et al.*, 2024). Despite its significance, many small-scale sesame farmers in Tanzania continue to face low productivity, limiting their ability to maximize yields and income (Yadav *et al.*, 2022; Dimoso & Andrew, 2021). Globally, in 2020, sesame output was 6.8 million tons, with Africa producing 4.3 million tons (69.2% of global production), and Tanzania contributing 0.71 million tons (16.6% of global production) (NBS, 2020; Kitole & Utouh, 2023). Efforts by the government and private organizations to increase productivity, including the introduction of improved sesame varieties and fertilizer incentives, have yet to fully resolve these challenges (Tibamanya *et al.*, 2022). A deeper understanding of the factors influencing the adoption of improved sesame varieties and their effects on productivity in Tanzania is crucial to addressing these ongoing issues.

While numerous studies have explored the determinants of adopting improved sesame varieties (Kushahwah *et al.*, 2018; Vasanthan *et al.,* 2019; Myint *et al.,* 2020; Teklu *et al.,* 2021; Wacal *et al.,* 2021; Yadav *et al.,* 2022; Jyothi *et al.,* 2023; Kafando, 2023), none have specifically investigated this issue in Mtwara, Tanzania, and its impact on sesame productivity among small-scale farmers. This study seeks to fill this gap by assessing the effects of adopting improved sesame varieties on productivity in Mtwara, providing valuable insights to enhance agricultural practices and policy formulation in the region.

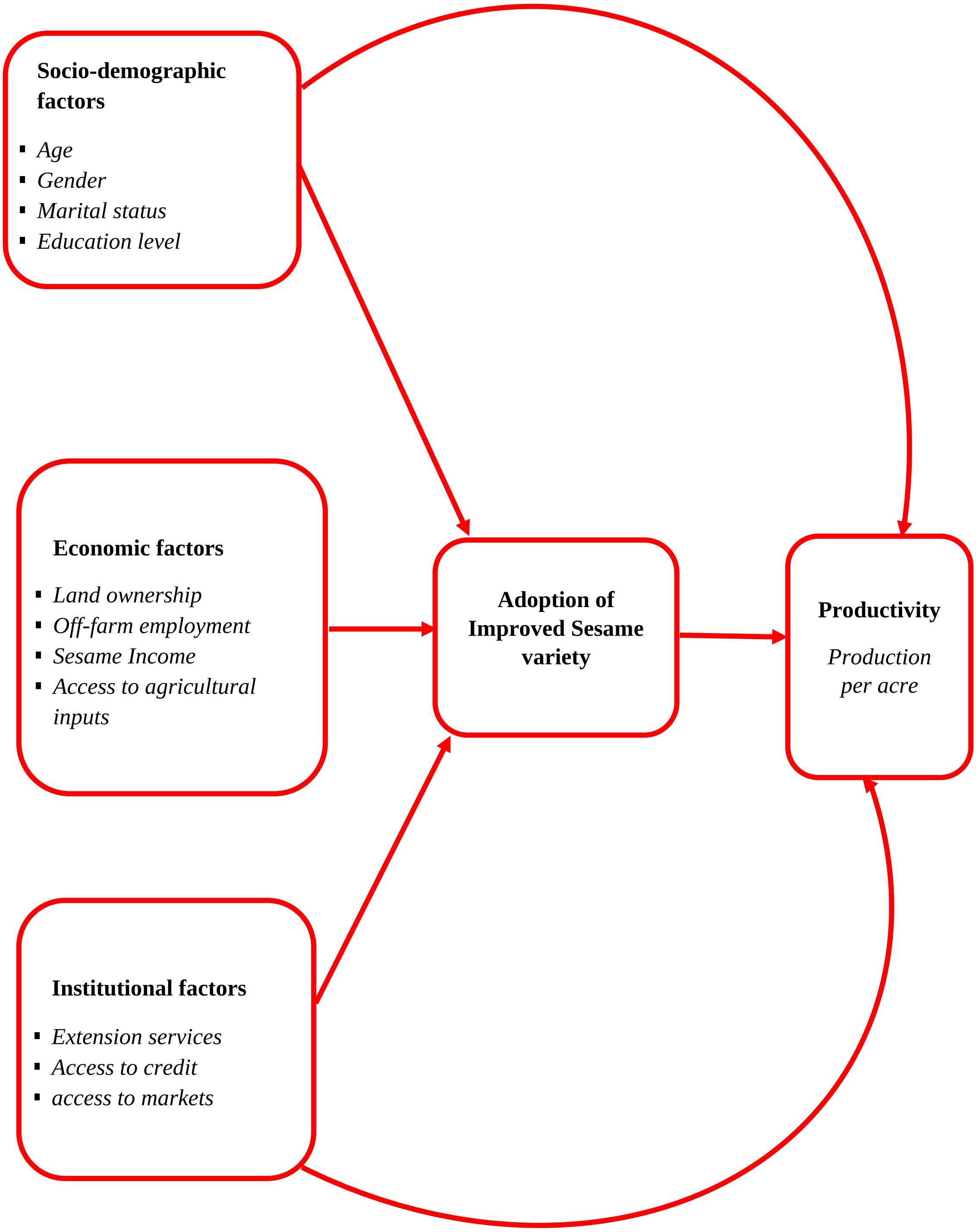
2. Theoretical foundations

This study draws upon two key theoretical frameworks: the Cobb-Douglas Production Function and Random Utility Theory, to analyze the factors influencing the adoption of improved sesame varieties among small-scale farmers in Mtwara, Tanzania.

The Cobb-Douglas Production Function, developed by Charles W. Cobb and Paul H. Douglas in 1928, is foundational in understanding the relationship between inputs and outputs within an economy (Varian, 1992). This theory provides insights into how variations in inputs such as labor and capital affect production levels. It assumes constant returns to scale, meaning that proportional increases in all inputs result in proportional increases in output. Additionally, it accounts for diminishing marginal returns, where the incremental output decreases as more of a single input is added, holding other inputs constant. Despite its limitations, such as the assumption of a linear relationship between inputs and outputs and the exclusion of factors like technological change, the Cobb-Douglas model remains a useful tool for analysing productivity trends. In this study, it is applied to examine how labor and capital inputs influence the productivity of sesame crops among small-scale farmers in Mtwara.

Random Utility Theory, formulated by Daniel McFadden in the 1960s, provides a framework for understanding decision-making processes when individuals face discrete choices, such as selecting among different products or services (Natenzon, 2019). The theory posits that individuals choose the option that maximizes their utility, which is shaped by the perceived benefits and drawbacks of each alternative (Kitamura & Org, 2018; Natenzon, 2019). While the theory assumes rational decision-making and consistent preferences, it does not fully account for cognitive biases, bounded rationality, or social influences. Despite these constraints, Random Utility Theory is instrumental in this study for analysing farmers' decisions to adopt improved sesame varieties. It suggests that farmers will choose the variety that offers the highest utility based on factors such as yield potential, resistance to pests and diseases, input requirements, market demands, and personal preferences. This theory helps illuminate the complex decision-making dynamics influencing the adoption of agricultural innovations in the region.

Figure 1: Conceptual Framework



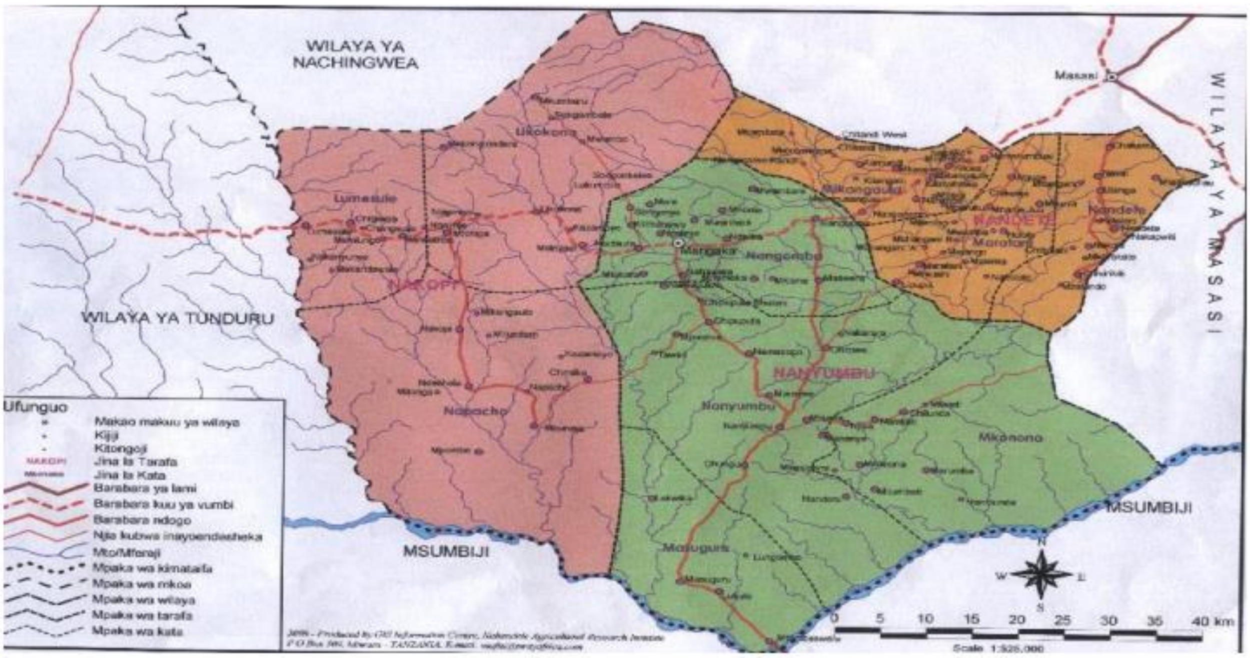
Source: Authors' Own Design (2024)

3. Methodology

This study employs a quantitative research approach rooted in the positivist paradigm to investigate the effect of adopting improved sesame seeds in Nanyumbu, Mtwara, Tanzania. A non-experimental, cross-sectional research design was chosen, allowing the researcher to observe and analyze data at a single point in time without manipulating any variables, aligning with the methodology (Cresswell, 2014; Anasel *et al.*, 2024; Kitole & Sesabo, 2024). This design is suitable for understanding the factors influencing the adoption of agricultural innovations among small-scale farmers in a real-world setting.

The research was conducted in the Mtwara region, specifically in Nanyumbu District, due to its significance as one of Tanzania's major sesame-producing areas. Mtwara's diverse agro-climatic conditions and substantial population of small-scale farmers make it an ideal location for examining the adoption of improved sesame varieties. The region's agricultural practices and its role in the national sesame production landscape provide a representative sample for this study. Nanyumbu District, located in the southeastern part of Tanzania, is particularly important due to its agrarian nature, with over 90% of the working population engaged in agriculture. This focus on Nanyumbu offers valuable insights into the factors affecting sesame cultivation and the adoption of improved varieties.

The unit of analysis for this study is small-scale sesame farmers, who are the primary stakeholders in sesame cultivation and are directly impacted by the adoption of improved sesame varieties. A simple random sampling technique was employed to ensure that each small-scale sesame farmer in the population had an equal chance of being selected (Kitole & Genda, 2024). The sample size was determined using a formula suggested by Kothari (2019), resulting in a sample of 150 head households of small-scale sesame farmers. This sample size was calculated based on a target population of 204,323 and an error margin of 7%, ensuring a sufficient degree of precision for the study's findings.



Source: District Executive Director's Office, Nanyumbu District, 2017

Table 1: Distribution of sample across different wards

WARD DIVISION	Number of respondents	Percentage
Mangaka	6	5.8
Nangomba	10	6.8
Lumesule	10	7.9
Likokona	12	5.8
Sengenya	15	5.8
Mnanje	15	6.8
Mikangaula	16	8.9
Maratani	20	10.0
Nandete	15	5.8
Mkonona	20	10.8
Nanyumbu	13	5.0
Chipuputa	10	6.8
Napacho	11	6.8
Masuguru	12	6.8
Total	**150**	**100**

Source: Researcher's Own Construct (2024)

Moreover, Table 1 presents the distribution of respondents across various wards in Mtwara. This distribution provides valuable insights into the geographic representation of the study, ensuring that data is collected from a diverse range of locations within the region. This broad coverage enhances the reliability and generalizability of the study's findings.

3.8.1 Econometric Model Specification of the Determinants and effects of Adoption of improved Sesame Varieties

3.8.2 Endogenous Switching Regression (ESR) Model

The endogenous switching regression (ESR) model is employed to address self-selection bias as used by Bidzakin *et al.* (2019). In the estimation of the Effect of Adoption of Improved Sesame Varieties on Productivity among Small-Scale Farmers, which reveals the drivers of adoption of improved sesame varieties among small-scale farmers. ESR is used for addressing self-selection bias.

It has been widely used to solve the problem of self-selection bias by many researchers in empirical analyses such as used by Bidzakin *et al.* (2019), Cao *et al.* (2021), Hendriks (2021), Murtazashvili and Wooldridge (2015), Suresh *et al.* (2021), Kitole *et al.*, (2024), and Tesfay (2020). Although the propensity score matching (PSM) is also used to address the issue of self-selection bias, it has the drawback that it is unable to address selection bias originating from unobserved factors (Murtazashvili & Wooldridge, 2015; Theodory & Kitole, 2024). The ESR model accounts for the self-selection bias and unobservable factors in the estimation by bringing in instrumental variable and counterfactual analysis (Liu *et al.*, 2021).

The estimation of the ESR model proceeds in two stages which are probit regression which is used in the first stage to determine the probability of adoption of improved sesame varieties and the second-stage regression estimates the productivity outcome, Nevertheless, this two-stage approach causes the problem of heteroskedastic residuals, which cannot be used to obtain consistent standards errors without cumbersome adjustments (Bidzakin *et al.*, 2019). Therefore, the full information maximum likelihood estimator is used to overcome the problem through a simultaneous estimation of the two stages involving one selection and two outcome equations (Bidzakin *et al.*, 2019).

ESR model is based on the assumption that individuals or households choose to either adopt improved sesame varieties or not adopt. Further, individuals are assumed to be risk neutrals and they take into account the expected benefit ($D_e{}^*$) derived from adopting improved sesame varieties and the expected costs ($D_n{}^*$) derived from not adopting improved sesame varieties. The difference in the expected benefits between adopting improved sesame varieties not adopting improved sesame varieties is defined as $D_i{}^*$, that is,$D_i{}^* = D_e{}^* - D_n{}^*$, then if $D_i{}^* > 0$, then the individuals adopt improved sesame varieties. However, *Di** cannot be observed, it can be expressed as a function of observable elements in the latent variable model as:

$$D_i{}^* = Z_i\theta + \mu_i \; with \; D_i = \begin{cases} 1 \; if \; D_i{}^* > \; 0 \\ 0 \; if \; otherwise \end{cases} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots . (2.0)$$

where *Di* is a binary variable which takes the value of 1 if a small-scale farmer adopts improved sesame varieties and 0 otherwise; *Zi* is a vector of factors influencing the adopting improved sesame varieties; α is a vector of unknown parameters to be estimated; and μ_i is an error term assumed to be normally distributed with zero means. Accordingly, two separate outcome equations are specified for adopting improved sesame variety and non-adoption of sesame variety:

Regime 1 (adopting improved sesame variety)

$$Y_{ei} = X_i\beta_{ei} + \mu_{ei} \; if \; D_i = 1 \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (3a)$$

Regime 2 (non-adoption of improved sesame variety)

$$Y_{ni} = X_i\beta_{ni} + \mu_{ni} \; if \; D_i = 0 \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots .. (3b)$$

where *Yei* and Y_{ni} are outcomes, X_i is a vector of exogenous variables that may impact the outcomes employed; μ_{ei} and μ_{ni} are random disturbance terms associated with the outcome variables. While the variables *Zi* in the selection equation (2) and variables X_i in the outcome equations (3a) and (3b) are allowed to overlap. In this case, the selection equation (2) is estimated based on all explanatory variables specified in the outcome equations (3a) and (3b) plus one instrumental variable. The valid instrumental variable is required to influence the choice of adopting improved sesame variety (Liu et al., 2021).

The three error terms μ_i, μ_{ei} and μ_{ni} in equations (2), (3a) and (3b) are assumed to have a triumvirate normal distribution with zero mean and covariance matrix:

$$\sum . = \begin{bmatrix} \sigma^2{}_n & \sigma_{en} & \sigma_{nm} \\ \sigma_{en} & \sigma_e{}^2 & . \\ \sigma_{nm} & . & \sigma^2{}_n \end{bmatrix}$$

where $\sigma^2{}_n$ is a variance of the error term in the selection equation (2.0), and $\sigma_e{}^2$ and $\sigma^2{}_n$ are the variances of the error terms in the outcome equations (3a) and (3b); σ_{en} is a covariance of

μ_i and μ_{ei}, and $\sigma_{n\eta}$ is a covariance of μ_i and μ_{ni}. Note that Y_{ei} and Y_{ni} are not observed simultaneously, which implies that the covariance between μ_{ei} and μ_{ni} is not defined and is therefore indicated as dots in the covariance matrix (Akpalu and Normanyo, 2014). Considering that the error term of the selection equation (2) is correlated with the error terms of the outcome equations (3a) and (3b), the expected values of the error terms μ_{ei} and μ_{ni} conditional on the sample selection is non-zero and are defined as:

$$E[\mu_{ei}|D_i| = 1.] = \sigma_{e\eta}\frac{\oint (Z_i\alpha)}{\phi(Z_i\alpha)} = \sigma_{e\eta}\lambda_{ei} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots. (4a)$$

$$E[\mu_{ni}|D_i| = 0.] = \sigma_{n\eta}\frac{\oint (Z_i\alpha)}{1-\phi(Z_i\alpha)} = \sigma_{n\eta}\lambda_{ni} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots. (4b)$$

where $\oint$ (•) and ϕ (•) are the standard normal probability density function and normal cumulative density function, respectively, $\lambda_{ei} = \frac{\oint (Z_i\alpha)}{\phi(Z_i\alpha)}$ and $\lambda_{ni} = \frac{\oint (Z_i\alpha)}{1-\phi(Z_i\alpha)}$. If the estimated covariance $\hat{\sigma}_{e\eta}$ and $\hat{\sigma}_{e\eta}$ are statistically significant, then the adoption of improved sesame variety and the outcomes are correlated. It implies that there is evidence of endogenous switching and the null hypothesis indicating the absence of sample selectivity bias is rejected. Specifically, the ESR model addresses the selectivity bias issue resulting from unobserved factors as a missing variable problem (Liu *et al.*, 2021). After the selection equation is estimated, the inverse Mills ratios (λ_{ei} and λ_{ni}) and the covariance terms ($\hat{\sigma}_{e\eta}$ and $\hat{\sigma}_{e\eta}$) are calculated and taken back to equations (3a) and (3b). In this regard, the inverse Mills ratios (λ_{ei} and λ_{ni}) control for selectivity bias resulting from unobservable factors.

Following Bidzakin *et al.* (2019), the coefficients from the ESR model is employed to calculate the average treatment effect on the treated (ATT). The observed and unobserved counterfactual outcomes for adopting improved sesame variety are presented in equation 5, given that productivity (number of bags produced per acre) through adopting improved sesame variety (observed):

$$E[Y_{ei}|D_i| = 1.] = X_i\beta_{ei} + \sigma_{e\eta}\lambda_{ei} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots. (5a)$$

Productivity (number of bags produced per acre) through non-adoption of improved sesame variety (counterfactual):

$$E[Y_{ni}|D_i| = 1.] = X_i\beta_{ni} + \sigma_{n\eta}\lambda_{ei} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (5b)$$

where equation (5a) is the expected number of bags produced through adoption of improved sesame variety. Equation (5b) is the counterfactual expected outcome of a non-adoption of improved sesame variety.

Thus, Following Tesfay (2020), the expected number of bags produced per acres in equations (5.0a) and (5.0b) are used to derive unbiased treatment effects (ATT):

$$ATT = E[Y_{ei}|D_i| = 1.] - E[Y_{ni}|D_i| = 1.] = X_i(\beta_{ei} - \beta_{ni}) + \lambda_{ei}(\sigma_{e\eta} - \sigma_{n\eta}) \dots\dots\dots (6)$$

On the other hand, the variables and their corresponding measurements used in this study are detailed in Table 2. This description and measurement framework provide a clear understanding of how each variable is operationalized, ensuring consistency and accuracy in data collection and analysis.

Table 2 Definition and Measurement of variables

Variable Name	Variable Type	Operational Definition	Expected Sign
Dependent Variable			
Productivity	Continuous	Number of bags produced per acre	
Adoption of improved sesame variety	Binary	1 = Yes, 0 = Otherwise	
Socio-Demographic Characteristics			
Age	Continuous	Age of household head in years	+
Gender	Dummy	1 = Male, 0 = Female	+
Marital status	Dummy	1 = Married, 0 = Unmarried	+/-
Education level	Categorical	0 = No education, 1 = Primary education, 2 = Secondary education, 3 = Tertiary education	+
Economic Factors			
Land ownership	Dummy	1 = Own land, 0 = Tenure	+/-
Off-farm employment	Dummy	1 = There is off-farm employment, 0 = No off-farm employment	+/-
Income	Continuous	Amount of money in TZS	+
Access to agricultural inputs	Dummy	1 = If agricultural inputs are accessible, 0 = Otherwise	+
Institutional Factors			
Extension services	Continuous	Number of extension services per year	+
Access to credit	Dummy	1 = If credits are accessible, 0 = Otherwise	+
Access to market	Dummy	1 = If access to market, 0 = Otherwise	+

Source: Authors' construction (2024)

4. Results and Discussion

4.1 The Descriptive Analysis of Demographic Characteristics among Small-Scale Sesame Farmers in Mtwara.

Results in Table 3 present the distribution of demographic characteristics among small-scale farmers in Mtwara, Tanzania. The data reveal that males are more actively involved in sesame production, representing 63.33% of the sample, compared to 36.67% female participants. Age distribution shows that the largest group of respondents, 33.33%, falls within the 26-35 age range, followed closely by 26.66% in both the 15-25 and 36-45 age brackets. Marital status data indicate that 62.00% of respondents are married, while 38.00% are single. Regarding educational attainment, 44.66% of respondents have completed primary education, 22.66% have no formal education, 18.00% possess tertiary or university qualifications, and 14.66% have secondary education.

Table 3 Demographic characteristics of respondents

Characteristics	Attributes	No. of Respondents (N=150)	Percentage (%)

Sex	Female	55	36.67%
	male	95	63.33%
	Total	**150**	**100.00%**
Age	15-25	40	26.66%
	26-35	50	33.33%
	36-45	40	26.66%
	46-55	12	8.00%
	56+	8	5.33%
	Total	**150**	**100.00%**
Marital status	Single	57	38.00%
	Married	93	62.00%
	Total	**150**	**100.00%**
Educational level	No education	34	22.66%
	Primary	67	44.66%
	Secondary	22	14.66%
	Tertiary level and university	27	18.00%
	Total	150	**100.00%**

Source: Research findings (2024)

The results in Table 4 indicate that the majority of small-scale farmers in Mtwara, 67.13%, predominantly use local sesame varieties, highlighting a strong preference for traditional seeds. A smaller proportion, 27.90%, utilize both improved and local varieties, suggesting some adoption of improved seeds but still with reliance on traditional options. Only 13.33% of the farmers exclusively use improved sesame varieties, indicating limited uptake of these newer, potentially more productive seeds. This distribution reflects the challenges in fully transitioning small-scale farmers to improved sesame varieties, which could be due to factors such as access, cost, or familiarity with traditional practices.

Table 4: Description on types of Sesame varieties used by Small-Scale Farmers in Mtwara.

Types of Sesame varieties	Number of famers	Percentage
Local sesame varieties	90	67.13%
both improved and local varieties	41	27.90%
Improved sesame varies	19	13.33%
Total	**150**	**100.00%**

Source: Research findings (2024)

4.3 The Effect of Adoption Decision of Improved Sesame Varieties on Productivity Among Small-Scale Farmers in Mtwara

Results in Table 5 reveal the distinct factors influencing productivity among small-scale farmers in Mtwara, Tanzania, based on their adoption of improved sesame varieties. For adopters, key drivers of productivity include farm or land ownership, which boosts productivity by 7.29 units, access to credit with a 6.97-unit increase, and access to markets, which enhances productivity by 5.66 units—each significant at the 10% level. Additionally, higher sesame income is linked to a 0.14-unit rise in productivity. In contrast, for non-adopters, productivity is positively influenced by age, with a coefficient of 1.221, while marital status and education level contribute significantly, with coefficients of 20.50 and 13.8371, respectively. The most substantial impact for non-adopters comes from access to agricultural inputs, which increases productivity by 30.71 units. These findings indicate that for adopters, access to resources such as land, credit, and markets plays a critical role in enhancing productivity, while for non-adopters, personal demographics and access to agricultural inputs are the primary factors. The study's results align with Gidabedi *et al.* (2023), who found that financial access, such as credit availability, is a key driver in farmers' adoption of new varieties and agricultural technologies.

Table 5: factors comparison between adaptors and non-adaptors

Variable	Adaptors		Non adopters	
	Coefficient	Standard Error	Coefficient	Standard Error
Gender	-2.689508	3.752584	-4.034234	5.339573
Age	0.0972298	0.2413559	1.221***	0.3810536
Marital status	3.366516	4.117149	20.50 ***	5.973591
Education level	0.9362279	2.266017	13.8371*	7.953016
Off farmer employment	0.2069683	3.068565	1.984793	6.931277
Farm or land ownership	7.292059*	4.593858	3.498096	5.210642
Access to credit	6.972277*	4.554765	-8.305447	5.870153
Access to agricultural inputs	1.650151	5.439044	30.71***	7.034454
Access to market	5.657741*	3.883498	1.820045	4.900912
Income	0.144452*	4.564565	1.98854	4.89122
Constant	37.45538***	13.57798	46.19 ***	13.33356

****p<0.01(10%), **p<0.05(5%), *p<0.1(10%)*

Source: Research findings (2024)

4.3.2 The Effect of adoption decision of improved Sesame varieties on Productivity among Small-Scale Farmers in Mtwara

The T-test comparison offers a detailed statistical analysis of the impact that adopting improved sesame varieties has on productivity among farmers in Mtwara, Tanzania. The analysis reveals a significant difference in productivity, measured in bags of sesame produced per acre, between those who have adopted these improved varieties and those who have not. Specifically, farmers who adopted improved sesame varieties achieved a mean productivity of 72.292 bags per acre, significantly higher than the 34.981 bags per acre recorded by non-adopters. The mean difference of 37.9396 bags per acre, coupled with a p-value of 0.000, indicates a highly significant improvement in productivity attributed to the adoption of these improved varieties. This finding underscores the substantial boost in productivity that can be achieved through the adoption of improved agricultural practices, making a strong case for the promotion of such interventions.

Table 6: T-Test for Adopters and Non-Adopters

Variable	N	Mean	Std. Error	Std. Deviation	p-value
Adopters	150	72.9206	10.2013	18.6658	
Non-Adopters	150	34.9810	10.9337	18.2170	0.000
Difference (Adopters - Non-Adopters)	150	37.9396	11.2367	19.3130	

Pr(|T| > |t|) = 0.000

Source: Research findings (2024)

Furthermore, these results align with the findings of studies conducted by Woyessa (2022), Nzunda (2023), and Mmasa (2022), which also observed significant differences in income levels between adopters and non-adopters of agricultural innovations. The analysis highlights the key factors influencing productivity, revealing that variables such as access to credit and farm ownership have varying effects on productivity depending on whether farmers adopt improved varieties. This distinction emphasizes the importance of providing targeted support to farmers, particularly in enhancing access to credit and securing land ownership, to maximize the benefits of adopting improved agricultural technologies and ultimately boost productivity.

5. Conclusion and Recommendations

This study examined the impact of adopting improved sesame varieties on productivity among small-scale farmers in Mtwara, Tanzania. The findings reveal that the majority of farmers continue to rely on local sesame varieties, with only a small proportion adopting improved varieties. The analysis identified key factors influencing productivity for both adopters and non-adopters. For those who adopted improved varieties, productivity was significantly enhanced by factors such as farm or land ownership, access to credit, market access, and income levels. In contrast, non-adopters' productivity was more influenced by demographic factors such as age, marital status, education level, and access to agricultural inputs. The study clearly demonstrates that the adoption of improved sesame varieties leads to substantial increases in productivity, underscoring the critical role of resources like credit, market access, and land ownership in driving these improvements. These findings are consistent with previous research, highlighting the importance of financial access and market connectivity in promoting the adoption of new agricultural technologies.

To further boost productivity through the adoption of improved sesame varieties, several recommendations are proposed. Policymakers should focus on promoting the widespread adoption of these varieties by enhancing extension services, offering targeted training, and providing financial incentives such as subsidies or low-interest loans for purchasing seeds and inputs. Additionally, improving access to credit and expanding market opportunities are essential to support farmers in adopting new technologies. Addressing the needs of non-adopters is also crucial; efforts should include improving education, increasing access to agricultural inputs, and providing targeted support to older and less educated farmers. By implementing these recommendations, adoption rates can be increased, leading to improved productivity and greater economic benefits for small-scale farmers in Mtwara.

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