MAKERERE UNIVERSITY

ASSESSING THE TECHNICAL AND ECONOMIC EFFICIENCY OF FARMERS IN MAIZE PRODUCTION IN UGANDA

BY

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A THESIS SUBMITTED TO THE SCHOOL OF GRADUATE STUDIES IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE AWARD OF A MASTER OF AGRIBUSINESS MANAGEMENT DEGREE OF MAKERERE UNIVERSITY

OCTOBER 2024

DECLARATION

I, **Nandaula Joeria,** do hereby declare that this dissertation entitled ***Assessing the Technical and Economic Efficiency of Maize Production in Uganda*** is my original work and I state that it has never been submitted to this or any other university for any academic award.

Sign ....   Date 12/12/2024

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i

APPROVAL

This is to certify that this dissertation by **Nandaula Joeria** titled: *Assessing the Technical and Economic Efficiency of farmers in maize Production in Uganda* has been conducted and completed under my supervision as a university supervisor

Sign: ………………………………… Date: 12/12/2024

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Sign: ………………………………… Date: 12/12/2024

DR. STEPHEN LWASA

ii

DEDICATION

I dedicate this piece of scholarly work first to the Almighty Allah and to my parents, my husband Mr. Fred Ndaula for the tireless efforts they dedicated to my physical, moral and emotional development as well as my education. Their passion and commitment encouraged me to pursue my own path to academic excellence leading to this milestone.

ACKNOWLEDGEMENTS

I acknowledge and thank my Supervisors, Assoc. Prof. Fredrick Bagamba, and Dr. Stephen Lwasa for the tireless scholarly guidance she offered during the entire research process. Without their support, the task of preparing and producing this dissertation would have proved insurmountable. I also, in the same spirit, acknowledge the College Agriculture & Environmental Sciences for offering me the program.

Furthermore, I acknowledge the support of Prof. Elepu Gabriel, Head of Agribusiness Management for his encouragement and academic support right from the beginning of the program. In the same light, I would like to commend the contribution of other lecturers for their tireless efforts towards completion of the program.

Thank you all.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABREVIATIONS AND ACRONYMS

AE	:	Allocative Efficiency
CGIAR	:	Consortium of International Agricultural Research Centers
DEA	:	Data Envelopment Analysis
EE	:	Economic Efficiency
FAO	:	Food and Agriculture Organization
FAOSTAT	:	Food and Agriculture Organization Corporate Statistical Database
MAAIF	:	Ministry of Agriculture, Animal Industry and Fisheries
MLE	:	Maximum Likelihood Estimation
NARO	:	National Agricultural Research Organization
OLS	:	Ordinary Least Squares
SCF	:	Stochastic Cost Function
SFPF	:	Stochastic Frontier Production Function
SSA	:	Sub-Saharan Africa
TE	:	Technical Efficiency
UBoS	:	Uganda Bureau of Statistics
UNPS	:	Uganda National Panel Survey
USAID	:	United State Agency for International Development
WFP	:	World Food Programme

ABSTRACT

Like other developing countries, agriculture in Uganda plays a pivotal role in economic growth, poverty alleviation, employment creation, foreign exchange earnings and food security. Maize, a priority crop in Uganda is dominated by smallholder farmers, with low levels of technical and economic efficiency. Given its significance, the Ugandan government has identified maize as one of the 15 priority commodities under the National Development Plans. However, despite its critical role, the country continues to struggle with low productivity, partly due to inefficiencies in both technical and economic aspects of maize production. This study aimed to offer a more comprehensive and precise understanding of the level and factors influencing technical and economic efficiency in maize production by analyzing these efficiencies over multiple time periods and across diverse geographical regions. The main objective of the study was to assess the technical and economic efficiency of maize farmers in maize production. the specific objectives were; (i) to estimate technical efficiency of farmers in maize production, (ii) To determine economic efficiency of farmers in maize production, and (iii) To determine the factors affecting the technical and economic efficiency of farmers in maize production in Uganda. The study utilized secondary data from the Uganda National Panel Survey (UNPS), collected by the Uganda Bureau of Statistics (UBOS) between 2013/2014 and 2019/2020. A sample of 8,386 maize farming households was analyzed to evaluate their technical and economic efficiency. Descriptive statistics, translog production function and Tobit regression were used to analyze the data. The results indicated technical efficiency of 56.7% suggesting that farmers could still improve output by 43.3% while, the mean economic efficiency of maize farmers was 9.6% implying that farmers can still reduce input costs by up to 90.4% while maintaining the same output. Tobit model results revealed that distance travelled by smallholder maize farmers from their households/farms to feeder roads, age of household head, household size, and education has a significant effect of the level of technical efficiency while education, household size, and all distances with exception of the distance travelled by smallholder maize farmers to the access the agricultural input markets had a significant effect on economic efficiency. Based on the study's findings, the study recommends improvement in road access, investment in education and strengthening extension services.

CHAPTER ONE

INTRODUCTION

1.1 Introduction

Africa's rural population to a large extent depends on farming (Giller, *et al.* 2021). Therefore, agricultural growth should be a core component of any development strategy that aims at reducing poverty and hunger (Abdulai & Abdul, 2017). Like other developing countries in Africa, agriculture in Uganda plays a pivotal role in economic growth, poverty alleviation, employment creation, foreign exchange earnings and food security (Pawlak & Kołodziejczak, 2020).

Despite its importance, however, food insecurity remains a persistent challenge in the country. This issue is partly linked to inefficiencies (technical and economic) in agricultural production, particularly among smallholder farmers who make up over 96% of Uganda's farming population (Kanu et al., 2014). Smallholder farmers, including maize farmers, often face issues such as incorrect application of inputs (Prabakaran, Vaithiyanathan & Ganesan, 2018) such as seed, and improper use of available resources, ultimately lowering technical efficiency.

Further technical inefficiencies by smallholder maize farmers in Uganda may stem from other factors which among include; inadequate technical knowledge among farmers. In many regions, farmers lack access to extension services or training on best agricultural practices, leading to inefficiencies in planting techniques, pest control, and crop care, which ultimately lower technical efficiency (Bahta, Jordaan, & Sebastian, 2020). Additionally, ineffective resource use, such as labor inefficiencies, also contributes to low productivity. Here mismanagement of labor or insufficient labor during critical farming stages, such as planting and harvesting, limits output. Furthermore, poor planning is another factor that reduces technical efficiency.

Where delayed planting, improper fertilization timing, or failure to implement timely pest management result in lower yields and diminished productivity (Gwebu & Matthews, 2018).

Economic inefficiencies, on the other hand, arise from challenges such as Limited market knowledge where lack of awareness of market prices or demand trends may result in missed opportunities for profit maximization. Additionally, Inefficient input use where even when the necessary inputs are available, sub optimal use of resources may result into low yields ultimately leading to less profitability.

Therefore, understanding and addressing these issues is critical for improving productivity and income among smallholder maize farmers in Uganda. For example, it's essential for smallholder farmers to know proper use of inputs such as fertilizers which is essential to maximize yields. If fertilizers are applied incorrectly, either in the wrong amounts or at suboptimal times, it can lead to nutrient imbalances, wasted resources, and reduced yields. Misuse of inputs further exacerbates challenges like soil degradation, which can reduce long-term productivity

Additionally, inadequate technical knowledge further exacerbates these problems which farmers need to know. Where without proper training, farmers may struggle to use available resources like seeds, fertilizers, and pesticides effectively. Adopting efficient practices is therefore key to boosting productivity and fostering sustainable farming practices that benefit both households and communities.

Also Planning is another critical area for farmers to address so as they can enhance their technical efficiency. Effective planning ensures optimal use of resources, timely crop harvesting, and better preparedness for unpredictable events, such as weather fluctuations or pest outbreaks.

From an economic perspective, Awareness of market prices and demand trends enables farmers to sell their produce at the right time and in the right markets, maximizing profits. This is particularly important in contexts where maize prices are volatile. By addressing these inefficiencies, smallholder maize farmers can improve their profitability, secure their livelihoods, and contribute to national food security.

The low technical efficiency levels (ranging from 60% to 80%) of Ugandan smallholder farmers partly results to low productivity that ranges between 1.5-2.5 tons per hectare. This is significantly lower than the average yields of other countries in the region. For example, in Kenya, maize yields are higher, averaging around 2.8–3.5 tons per hectare under smallholder systems, while in Tanzania, productivity is approximately 1.8–2.7 tons per hectare depending on agroecological zones and farming practices. Comparatively, the average maize productivity in sub-Saharan Africa is estimated at 2.0 tons per hectare, well below the global average of approximately 5.7 tons per hectare.

Regarding economic efficiency, smallholder maize farmers in Uganda typically operate with an economic efficiency score ranging between 60% and 70% (Nin-Pratt & McBride, 2024). This suggests that farmers are utilizing only 60% to 70% of their potential, leaving room for 30% to 40% improvement in resources allocation and cost management.

In contrast, maize farmers in other countries such as South Africa and Kenya operate at higher efficiency levels, resulting in better yields (Manda et al., 2022). For example, the technical efficiency of smallholder maize farmers in South Africa is estimated at around 85%, reflected in average yields of 5.5 tons per hectare (Van Zyl et al., 2023).   In Kenya, the technical efficiency of maize farmers ranges from 75% to 85%, translating to an average yield of approximately 3.3 tons per hectare (Muriithi et al., 2022).

Uganda not only lags behind in terms of low technical efficiency levels among smallholder maize farmers but also falls short compared to farmers growing other cereals, such as rice and wheat. For instance, rice farmers in Northern and Eastern Uganda achieve technical efficiency levels ranging from 70% to 85%, while wheat farmers in Western Uganda reach levels between 70% and 90% (Kabeja et al., 2020; Okwakol et al., 2021). These disparities underscore the potential for improvement in yields of major staples, among which include, maize

Maize is the major cereal crop which in Africa according to Monsanto (2014) is consumed directly and serves as a staple diet for about 300 million people and indirectly as part of animal feeds. In Sub-Saharan Africa, maize is virtually grown in all parts and is considered as an important cereal crop to the natives (Abdulaleem *et al.*, 2019). In Uganda, the crop is a dominant staple crop which contributes significantly to consumer diets and serves as a major staple food for low-income earners in rural and urban areas.

The crop also provides a varied diet to households and institutions (schools, prisons, factories, among others), in form of roasted green cobs, steamed green cobs, and maize flour prepared as posho, (Tadeo *et al.*, 2018) and has greatly gained importance in respect of poverty reduction and food security in Uganda (Okello *et al.*, 2019).

Recognizing its importance, the Ugandan government has included maize among the 15 priority commodities under the National Development Plan III and has identified it as the only cereal crop to be promoted under the revised Development Strategy and Investment Plan (DSIP) of the Ministry of Agriculture, Animal Industry, and Fisheries (Shinyekwa *et al.*, 2023).

Despite all its importance, maize production is constrained by inefficiencies, resulting in low yields (1.5-2.5 tons per hectare) that cannot satisfy the needs of the growing population, i.e., 3.2 % per annum (UBOS, 2017). Understanding and addressing these inefficiencies is crucial for the sustainability of maize production systems in the country as well as closing the yield gap (Okoboi *et al.*,2023).

1.2 Problem Statement

Despite continuous efforts by the Ugandan government, private sector, and other stakeholders to enhance maize production, yields have remained disappointingly low. Although maize production peaked at 2.8 million tonnes in 2017 (Epule, Ford & Lwasa, 2017), growth has since stagnated, with farm level yields ranging between 1.5 and 2.5 tonnes per hectare, significantly below potential yield of 7tonnes per hectare (Kepher, M. 2020). This persistent yield gap raises critical concerns about the efficiency with which smallholder maize farmer utilize available resources, given government support. Several factors, including farmers' education levels, access to credit, soil quality, and weather conditions, can influence crop yields. However, beyond these factors**,** understanding how efficiently farmers allocate and use their inputs is essential to identifying practical ways of improving efficiency.

Numerous studies have investigated the technical efficiency of farmers in developing countries like Uganda (see for example, Hyuha *et al.,* 2017; Bagamba, *et al.,* 2007 Nakanwagi and Hyuha, 2015; Kalule and Ssebbale, 2014; Okwir, 2019; Obwona, 2016; Muhindo, 2018; Mutambira, 2019 among others), while other studies focused on economic efficiency, and these included studies by Nkonya *et al.* (2016) and Okwera *et. al.* (2021), who examined factors influencing economic outcomes in maize production.

However, few studies have analyzed both technical and economic efficiencies within Uganda's maize sector. Notably, while previous studies, by Okwera et al. (2021), assessed both technical and economic efficiency their research was limited by their use of cross-sectional data.

The current study addresses this gap by utilizing panel data, that accounts for household heterogeneity which enables to obtain consistent estimates of coefficients and efficiency scores.

1.3 Objectives of the study

1.3.1 Main objective

The main objective of the study was to assess the technical and economic efficiency of farmers in maize production in Uganda.

1.3.2 Specific objectives

i. To estimate technical efficiency of farmers in maize production
ii. To determine economic efficiency of farmers in maize production
iii. To determine the factors affecting the technical and economic efficiency of farmers in maize production in Uganda.

1.4 Research Hypothesis

Ho1. Maize farmers in Uganda are technically efficient

Ho2. Maize farmers in Uganda are economically efficient

Ho3. The distance traveled by smallholder maize farmers from their households or farms to access feeder roads has a positive and significant impact on their technical efficiency.

Ho4. The distance traveled by maize farmers from their households or farms to reach agricultural extension services has a positive and significant effect on the level of economic efficiency.

Ho5. Education has a positive and significant effect on the level of economic efficiency.

1.5 Justification of the Study

Maize is a staple food in Uganda, and improving efficiency and productivity in its production is crucial for ensuring nation food security (Montalbano, Pietrelli & Salvatici, 2018). Despite government investments in agricultural development, many households continue to experience food insecurity (Whitney et al. 2017). Given that domestic maize supply has not kept pace with domestic demand, it is essential to examine factors such as the gender of house hold head, education level, household size, age of household head, among others, that influence efficiency and productivity of maize farming. Understanding these factors can guide the formulation of targeted policies, such as improving agricultural extension services, enhancing access to production inputs and machinery, and regulating maize exportation. These measures can help reduce poverty and food insecurity by encouraging greater maize production, even among non-farming households.

Additionally, this study will contribute to the existing research, motivating further studies that could build on its findings and recommendations, thus continuing to fill the knowledge gap in this area

1.6 Scope of the Study

The study was limited to measuring technical and economic efficiency of smallholder maize farmers in Uganda. It utilized data from Uganda National Panel Survey (UNPS) provided by

Uganda Bureau of Statistics (UBOS) to identify the factors influencing these efficiencies. The data spanned four survey waves conducted during years 2013/2014, 2014/2015, 2017/2018 and 2019/2010. The study specifically targeted smallholder maize farmers of Central, Eastern, Western and Northern regions of Uganda.

1.7 Theoretical frame work of Technical and Economic Efficiencies

This section explains the concepts of both production and efficiency and how the two concepts help us to understand the relationship between inputs and output of a given firm. For example, a maize farm is employing two inputs, namely X_1 (quantity of fertilizer) and X_2 (amount of seeds) in the production of one output Y_i (yield of maize of the i^{th} farmer). The explanation can diagrammatically be illustrated on a graph showing technical, allocative and economic efficiencies in figure 1 below;

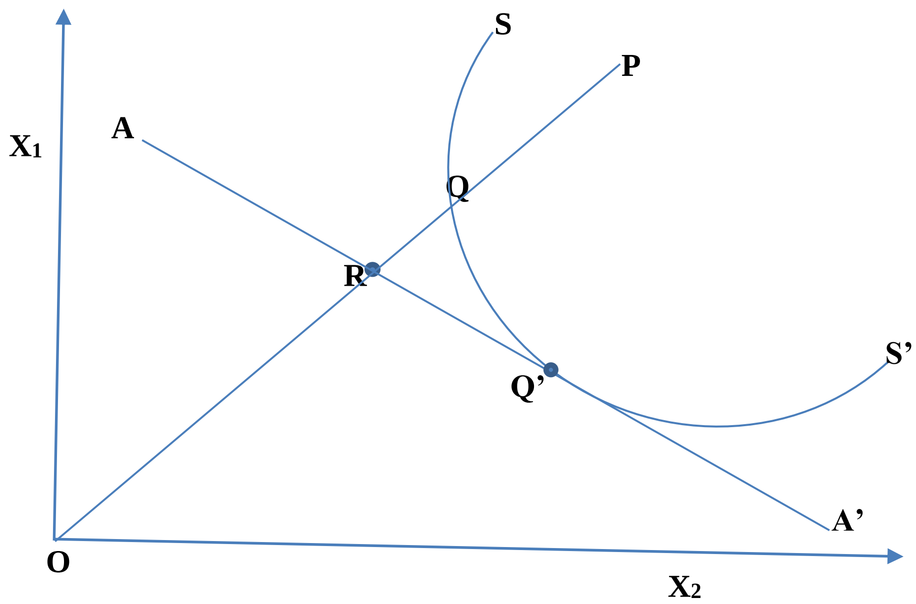

Figure 1: The diagram above represents Technical, allocative and economic efficiencies (adopted from Kamau, 2019; Coelli, 2016)

From Figure 1, a firm operating at Q is technically efficient because it is operating on the isoquant S-S'. However, if a firm is operating at P, it is not efficient because it is far away from Q and in this regard the technical inefficiency of P is represented by the distance QP, indicating the extent to which the firm's inputs can be proportionally reduced without reducing output. Thus, in a ratio form, the technical efficiency of this firm is measured by $TE_i = \frac{OQ}{OP}$ which is equal to $1 = \frac{QP}{OP}$. According to Chiona et al., (2014), technical efficiency takes values between zero and one. Thus, a technical efficiency of one implies that the firm is fully efficient (while zero efficiency implies the firm is technical inefficient).

From the diagram, the input price ratio is represented by the slope of the straight-line A-A'. With this, the AE of the firm can be determined.

At point P allocative efficiency is defined as the ratio $AE_i = OR$ since the distance RQ represents the reduction in (production) costs if production were to occur at the allocatively (and technically) efficient point instead of a technically efficient one but allocatively inefficient point Q.

Economic efficiency is a product of both technical (OQ/OP) and allocative efficiency ($\frac{\mathrm{OR}}{\mathrm{OP}}$) given by (OR/OP). This is due to the theoretical reduction in costs because of the decline of input proportions from P to R, as such, for a technically and allocative inefficient farmer to gain economic efficiency the farmer should produce at Q'. This is the point of tangency for both the isoquant curve and the isocost, which forms the optimal point. At this point, the farm exhibit both technical and allocative efficiency and therefore attains economic efficiency.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

This chapter presents literature review on efficiency in production, technical, and economic efficiency. In addition, methods of measurement of efficiency are reviewed. The empirical studies on technical and economic efficiency using the translog- production function and the translog cost function are critically reviewed. The final section presents factors that affect technical and economic efficiency.

2.1.1 Efficiency in production

To achieve the maximum output, farmers need to be efficient in resource allocation. Efficiency is defined by Farrell, (1957) as farmers' ability to produce maximum amount of output possible from given set of inputs. Efficiency measure according to Cordeiro (2018) can be defined as either the variation between the actual and the maximum expected output for a given inputs (output efficiency) or the difference between the actual and minimum expected input for given output (input efficiency). Efficiency can be attained technically through proper utilization of available set of inputs such as land, fertilizer, seed, labor among others. Also, efficiency in production can be achieved allocatively through cost minimization, or it can be attained both technically and allocatively resulting to economic efficiency.

2.1.2 Technical efficiency

Technical efficiency refers to the ability of a farm or producer to achieve the maximum possible yield or output from a given set of inputs (Timmer, 1970).It is the ratio of the least possible amount of inputs, compared to the actual amount of inputs, used for producing a given amount of output. Farrell (1957) further highlights that technical efficiency can be measured by two approaches; The input-oriented approach focuses on determining the extent to which inputs can be proportionally reduced without changing the level of output produced. The other approach is the output-oriented approach that seeks to answer the question "by how much can the amount of output be proportionally increased without changing the amounts of inputs used". Therefore, the study purposely focuses on an input -oriented approach since the primary objective of stallholder maize farmers is to minimize the inputs used while maintaining a consistent level of maize production. Further Given the high costs associated with agricultural inputs, understanding how to achieve better input efficiency could be crucial for enhancing the productivity of smallholder maize farmers. This orientation would allow to identify opportunities for resource savings without compromising output levels

2.1.3 Economic efficiency

According to Rao (2012) Economic efficiency refers to the optimal use of resources to maximize the value of output or profit, while minimizing the cost of production. Economic efficiency is achieved when the producer combines resources in the least cost combination to generate maximum output (technical) as well as ensuring least cost to obtain maximum revenue (Chukwuji, *et al.*, 2006).

2.2 Methods of measuring technical and economic efficiency

According to Okoye *et al.,* (2016), efficiency can be measured and estimated using two main approaches; The parametric approach, which employs econometric techniques and the non-parametric approach which lilies on mathematical programming techniques (Sarafidis, 2012). Speelman *et al.,* (2018) further noted that, the most widely used methods for efficiency analysis within these approaches are the Stochastic Frontier Analysis (SFA) for parametric models and the Data Envelopment Analysis (DEA) for non-parametric models.

2.2.1 The non- parametric approach (Data Envelopment Analysis)

The non-parametric model such as DEA model was developed by Charnes *et al.,* (1978) who carried on the seminal work of Farrel (1957) to incorporate many inputs and outputs simultaneously. The approach relies on mathematical programming and does not make assumptions regarding the distribution of inefficiencies or the functional form of the production function. Additionally, Karani-Gichimi *et al.,* (2015) assert that Data envelopment method does not impose functional forms on the production frontier, which is a conventional practice for the parametric stochastic frontiers.

DEA approach imposes some technical restrictions such as monotonicity and convexity (Kumbhakar *et al.,* 2010) creating room for a flexible frontier that enhance a functional form that is able to vary across all the Decision-Making Units (DMUs). Despite the limitations of the deterministic DEA method, the approach has advantage as it allows for the provision of information on input and output shadow prices of DMUs. It is also capable of handling multiple outputs and inputs, unlike SFA. However, DEA is not suitable for this study because, it lacks robustness over outliers and its deterministic form makes it impossible to test for hypothesis

(Chimai, 2011). Therefore, the parametric approach; specifically, the stochastic frontier is the main focus of this study.

2.2.2 The parametric approach (stochastic frontier production function)

The stochastic production function was used to assess the technical efficiency of maize farmers in Uganda. Coelli *et al.*, (2018) mentioned that, it is called a stochastic function because the output values are bounded by the stochastic (random) variable $exp(X_i\beta + V_i)$. Furthermore, the random error V_i can be positive or negative and therefore the stochastic frontier outputs vary about the deterministic part, $exp\ (X_i\beta)$of the model. The model separates the error term into a two-sided random error that accounts for random factors beyond the farmer's control and a one-sided inefficiency component. Additionally, it facilitates traditional hypothesis testing and permits a single-step estimation of inefficiency effects (Kumbhakar & Lovell, 2013). Because of variations in resource endowment, skills or knowledge, some farmers tend to be more efficient than others in production; therefore, SFA can be able to model these deviations. Therefore, this approach was used for this study due to its parametric nature and superiority over other methods. It also uses the method of maximum likelihood that gives more robust results as opposed to Data Envelopment Analysis (DEA) which relies on mathematical programming.

The stochastic frontier production function is defined by;

$$Y_i = f(X_i; \alpha_i) + \varepsilon_i$$

$$where, i = 1,2 \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots n$$

$$\varepsilon_i = V_i - U_i$$

Where Y_i is the maize output for the i^{th}farm, $f(X_i\beta)$is an appropriated production function like a Cobb Douglas or translog production of vector,X_i is a vector of inputs associated with the i^{th} farm for production of maize and β represents the unknown vector parameters to be estimated. ε_i is the composite error term which comprises of the random error term V_i and U_i. V_i measures the random variation in output (Y_i) due to factors outside the control of the farm (for example weather, natural disasters, pest and disease outbreaks among others), measures errors and other statistical noise. V_i is assumed to be identically and independently distributed as $N(0, \sigma_v^2)$ and independent of u_i which has a half normal non-negative distribution. u_i is independently, but not identically distributed. u_i is an inefficiency parameter which is one-sided error term that allows actual production to fall below the frontier. In otherwards, this variable hinders a certain farm from achieving maximum output because it is associated with farm factors. Therefore u_i captures the technical inefficiencies. Deviation of any farm from the frontier is a result of random errors and inefficiencies in production. u_i is therefore linked to the technical inefficiency of the maize farm and ranges between 0 and 1. n is the number of maize farmers that took part in the survey.

The technical efficiency of a maize farmer is defined as the ratio of the actual output to the maximum possible output (frontier output) given the quantity of resources employed by the farmer. Technical inefficiency, therefore, refers to the margin with which the level of output for the farmer falls below the frontier output.

$$TE_i = \frac{Y_i}{Y_{i^*}} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots..(1)$$

Where, TE_i is the maize production technical efficiency score of the i^{th} farm. Y_i is the observed output as specified in equation (1), and $Y_i^* = f(X_i\beta)$, is unobserved frontier output which assumes a technically efficient production (the highest predicted output for the i^{th} farm). Equation (3) is presented as;

$$TE_{ij} = \frac{f(x_i;\beta)\ exp\ (v_i - u_i)}{f(x_i;\beta) exp(v_i)}\ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots..(2)\text{(Actual output/Frontier output)}$$

This can be simplified to $TE_{ij} = exp^{(-u_{ij})}$since the actual production is usually less than the Frontier production$(Y_i \leq Y_{i^*})$.

Technical inefficiency ==1-TE……………………………………………………..………..(3)

2.2.3 The Stochastic Cost Function

Coelli et al. (2005) provide a comprehensive discussion on stochastic cost functions within the context of Stochastic Frontier Analysis (SFA). Their work emphasizes the use of these functions to model the inefficiencies in production processes and estimate the cost efficiency of firms or farms. The stochastic cost function gives the minimum level of cost at which it is possible to produce some level of output, given input prices, which shows the minimum expenditure required to produce output (y) at input prices (w).

The analytical framework for the stochastic cost function used for the analysis of economic efficiency is specified by changing the error from the; $\varepsilon_i = v_i - u_i\ to\ \varepsilon_i = v_i + u_i$.

Transforming the production function gives us the cost function in general form as;

$$C_{ij} = F(W_i, Y_i; \beta) exp\pi_i\ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots..\ldots\ldots\ldots\ldots\ldots\ldots\ldots.(4)$$

Where C_i is the minimum cost of maize production by the i^{th} farmer with the corresponding outputY_i.$w_i$is the vector of input prices for the i^{th} farmer and β represents a vector of unknown parameters to be estimated, whereas π_i is the composite error term which can be decomposed into $v_i + u_i$. u_i is the inefficiency parameter responsible for cost inefficiency and it determines how far the farm operates above the cost frontier. v_i is the stochastic term associated with random variations in production. Note that the positive signs precede the error components because the inefficiencies are known to raise production costs (Ogundari & Ojo, 2007).

By decomposing the composite error terms, Eq. (4) can be restated as;

$$C_{ij} = F(W_i, Y_i; \beta) exp(v_i + u_i) \dots \dots \dots \dots (5)$$

EE would then be estimated as specified in Eq. (6)

$$EE = \frac{C_{ij}}{C_{ij}^*} \dots \dots \dots \dots (6)$$

where C_{ij} is the observed cost of the ith farm for production for the jth crop enterprise, while $C_{ij}^*$is the frontier cost of production for the jth crop enterprise which assumes an economically efficient production for the ith farm. Equation (6) can be restated as;

$$EE = \frac{F(W_i, Y_i; \beta) exp(v_i + u_i)}{F(W_i, Y_i; y) exp(v_i)} \dots \dots \dots \dots (7).$$

This can be simplified as $EE = \exp u_i$ which is the economic efficiency for the ith farm for the production of maize. Like technical efficiency, economic efficiency also takes on values between 0 and 1, with EE of 1 representing a cost- efficient farm.

2.2.3.1 Model specification of the stochastic frontier production function

Among the possible algebraic forms, the most popularly used functional forms of stochastic production function in many empirical studies of agricultural production analysis are Cobb-Douglas and the transcendental logarithmic (Translog) functional forms (Prokhorov, 2024).

According to Coelli, (1995) the Cobb-Douglas production function is attractive due to its simplicity and logarithmic nature of the production function. However, according to Wassihun *et al.* (2019) the Cobb- Douglas production function is less flexible as it imposes severe priori restrictions on the farm's technology by restricting the production elasticity to be constant. Whoever the translog production function has advantage of showing the effects of the interaction among input variables on the output unlike the Cobb-Douglas functional form.

Therefore, the study adopted a translog stochastic production frontier as it was used by other authors to assess the technical efficiency of crops (Martey *et al.* 2019; Thayaparan & Jayathilaka, 2020; Inkoom, Acquah & Dadzie, 2022). Additionally, according to Battesse (1992) a translog function form can be interpreted as a true representation of any underlying production frontier due to its flexibility.

Theoretically, the stochastic frontier translog production function can be specified as;

$$\ln Y_i = \beta_0 + \sum_{k=1}^{m} \beta_k \, lnx_{k_i} + \frac{1}{2}\sum_{k=1}^{m}\sum_{j=1}^{m} \beta_{k_j} \, lnx_{k_i} lnx_{ji} + v_i - u_i \quad \text{......(8)}$$

where

$ln =$ Natural logarithm

$y_i =$ Is the maize output of the ith farmer measured in Kg/Ha

$x_i =$ Is a vector of inputs

$ij =$ Are positive integers

$\beta's =$ Vector of parameters to be estimated

$v_i \; and \; u_i =$ These are the inefficiency error terms

2.2.3.2 Model specification of the stochastic frontier cost function

The study adopted a translog stochastic cost frontier as it was used by Dadzie, (2022) to examine drivers to technical, allocative and economic efficiencies in Cocoa farming in Ghana. The translog stochastic cost frontier function is used because of having advantage of showing the effects of the interaction among input prices on the total cost of production and it is flexible.

2.3 Determinants of Technical and Economic Efficiency of Maize Farmers

A Tobit model was used to determine the factors that affect technical and economic efficiency. This is the case of a limited dependent variable because the value of efficiency ranges from 0 to 1. Tobit model has been widely used to determine the factors affecting technical and economic efficiency as used by Tolesa, (2021), Okello *et al.*, (2019), Kifle *et al.*, (2017), Mustefa *et al.*, (2017), Kamau, (2019), Sihlongonyane *et al.,* (2014) among others. Various socio-economic and demographic variables were regressed to determine the factors affecting technical and economic efficiency.

Theoretically, the Tobit model can be specified as;

$$y_i^* = x_i\beta + \varepsilon_i \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (9)$$

Where y_i^* is a latent variable for the ith maize farm representing efficiency scores. x_i is a vector of independent variables hypothesized to influence technical and economic efficiency, The β's are parameters associated with the independent variables to be estimated. Then $\varepsilon_i$is the error term with an assumption of having an independent and normal distribution with zero mean and variance σ^2.

2.4 Empirical studies on technical and economic efficiency of maize production

Thayaparan & Jayathilaka (2020) conducted a study focusing on the technical efficiency of paddy farmers in Sri Lanka, using a translog production function. This advanced functional form allows for more flexibility in how inputs interact and affect output, making it well-suited for agricultural production studies. Their findings revealed inefficiencies among paddy farmers, suggesting a considerable potential to enhance production efficiency. The study’s emphasis on the inefficiency of farmers implies that many paddy farmers are not fully utilizing their inputs to achieve maximum possible output. The room for improvement suggested by the authors indicates that even with the same resources, better farming techniques and more efficient use of inputs could lead to significant yield increases.

The policy recommendation arising from this study focuses on the role of agricultural extension services, particularly encouraging the exchange of farming experiences between male and female farmers. The emphasis on gender-based experience-sharing indicates a recognition of potential differences in farming practices between genders, which could lead to cross-learning and improved efficiencies.

Additionally, the recommendation to provide additional income facilities for farmers is significant because financial resources are often a limiting factor for adopting new technologies or better practices. The study implies that income support could lead to better investment in inputs and farming technology, thus improving efficiency and farmer income over time.

Shah *et al* (2020) conducted a technical efficiency analysis of hybrid maize production in Punjab, Pakistan, and compared two popular functional forms: Cobb-Douglas and translog models. The study's key contribution is its emphasis on model comparison for efficiency estimation. The authors found that the translog model was more robust, with a mean technical efficiency of 94.10% compared to 81.06% from the Cobb-Douglas model. The higher technical efficiency indicated by the translog model suggests that the flexibility in capturing variable input elasticities and interactions among inputs provides a more accurate representation of maize production in Punjab.

The findings highlight the sensitivity of technical efficiency estimates to the choice of the functional form. The Cobb-Douglas model, while simpler, assumes constant elasticity of substitution between inputs, which may not always reflect reality in agricultural production. On the other hand, the translog model allows for variable elasticity, meaning the relationship between inputs and outputs can change, offering a more nuanced view of efficiency. This study emphasizes the importance of selecting appropriate models in efficiency analysis, as inaccurate specifications can misrepresent the true performance of farms and lead to misguided policy interventions.

Aminu, Suleiman & Abdu (2024) explored the economic efficiency of maize production among smallholder farmers in Nigeria. Using the translog cost function, the study assessed how different inputs (such as land, labor, and fertilizers) influenced maize production costs. The results revealed that while most farmers were technically efficient, there was room for improvement in allocative and economic efficiency. Policy recommendations included better access to extension services and input subsidies to reduce cost inefficiencies and improve overall productivity.

Elham *et al.* (2023) conducted a similar study in Ghana, focusing on the economic efficiency of maize farmers. They applied the translog cost function to capture the variable input relationships and their cost effects. Their findings indicated that maize farmers in the region were operating below optimal economic efficiency levels due to poor access to credit and extension services. The study recommended investment in rural infrastructure and financial services to boost the economic efficiency of maize production in Ghana.

CHAPTER THREE

METHODOLOGY

3.1 Research Design

The study adopted a quantitative research design relying on secondary data from the Uganda National Panel Survey (UNPS). These data were collected by the Uganda Bureau of Statistics (UBOS) with support from the World Bank between 2013/2014 and 2019/2020. The current study relied on the data capture method for reasons that the data collected by the Uganda Bureau of Statistics (UBOS) with support from the World Bank is of high quality, as both organizations adhere to rigorous methodologies and established protocols to ensure accuracy and reliability. Furthermore, the longitudinal nature of the Uganda National Panel Survey (UNPS), spanning the period from 2013/2014 to 2019/2020, provides valuable insights into trends and changes over time. This longitudinal design allows for the analysis of household heterogeneity among maize farming households, enabling the generation of robust and reliable efficiency score estimates.

3.2 Data and Sample Size

Data used by this study were collected during the Uganda National Panel Survey (UNPS). The Uganda National Panel Survey (UNPS) is a longitudinal survey conducted by the Uganda Bureau of Statistics (UBOS) with support from the World Bank. Its primary objective is to generate high-quality, nationally representative data that supports evidence-based policymaking and tracks development indicators over time. The survey employs rigorous methodologies, including multi-stage stratified sampling, to ensure reliability and representativeness. It collects detailed information on household demographics, income, agriculture, health, and other key sectors, making it highly relevant for analyzing agricultural efficiency at the household level.

The survey collects data on multiple modules, including household characteristics, agriculture, women's issues, and community facilities. For this study, data were utilized specifically from the household, agriculture, and community modules. The household module provided insights into household characteristics, including the household roster, educational attainment of household members, sex (male and female) and labor force status, The agriculture module gathered critical information on household land parcels, input usage, crops grown, types of seeds used, and agricultural output. The community module captured information on community facilities, such as roads, markets, and banks.

To ensure accurate seasonal data collection on maize output, enumerators made two visits to each household, that to say, one visit per season, each covering six months. This approach enabled them to gather data on both the previous and current seasons on maize productivity, enhancing the reliability of the information collected. The specific waves of the UNPS used in this study were waves 4, 5, 7, and 8, corresponding to the years 2013/2014, 2015/2016, 2018/2019, and 2019/2020, respectively. These waves were selected as they represented the most recent data available at the time of conducting the research. Wave 8 was the most recent one and wave 6 was not used due to a lot of missing data. Note that each wave had two periods (seasons A and B). To explain; the study adopted 4 waves with total of eight periods (seasons). There were variations in seasons according to their respective waves, for example wave 4 season A had 1,381 whereas season B had 1,023 observations; Then wave 5 season A had 1233 observation whereas season B had 1266 observations; also wave 7 season A had 759 number of observations whereas season B had 759 observations; lastly wave 8 season A had 869 number of observations whereas season B had 1096 number of observations. Therefore, data from these waves were merged to create a longitudinal dataset, forming an unbalanced panel of 8386 observations.

3.3 Data Processing and Management

Data processing involved several procedures to address missing data and outliers. Various methods have been developed to handle missing data. According to Kang (2013), some procedures include: deleting all observations with missing data, removing all variables that contain missing data, and substituting missing values with the mean of the respective variables. Additionally, missing values can be replaced with predicted values obtained from regressing selected variables on the variable with missing data, a method known as “regression imputation.”

Regression imputation helps fill these gaps by predicting the missing values based on relationships between variables in the observed data. In this method, a regression model is developed using the available data, and the missing values are estimated based on the predicted values from the model. STATA facilitates this process by allowing the creation of regression models that take into account other variables to impute missing data. The assumption is that the relationships between observed variables are strong enough to make reasonable predictions for the missing values, thus improving the completeness of the dataset for analysis.

Therefore, the study used the regression imputation approach to replace missing values using STATA statistical software. Imputing missing data requires that when the missing and observed values are compared, there are no consistent discrepancies (i.e., missing completely at random-MCAR) or missing at random (MAR) where although there are discrepancies between observed and missing data, these can be accounted for by other covariates (Kang, 2013). For this data, missing data was assumed to be MAR since the missing data (for example price data) was not due to non-response by survey respondents but was because households were not engaged in buying and selling.

Sample refreshment occurs when new participants are added to a panel to counteract attrition, as some respondents drop out over time. While this process helps maintain the representativeness of the survey, it leads to missing data, especially for variables that were consistently collected from the original participants but may not be available for the new entrants. This creates gaps in the dataset, contributing to missing data.

Further data transformation was undertaken. For example, dummy variables were generated prior to converting all input and yield variables into logarithmic variables for estimation of the stochastic frontier models for observations that had zero values for the respective inputs to be used in the regression. The inclusion of dummy variables (such as; used organic fertilizer, used inorganic fertilizer, used agricultural pesticide among others) in the regression model helped to capture the effects of categorical factors or binary conditions that would influence maize output. During log transformation in Stata, zero values were handled by adding a small constant (commonly 1) to the variable to avoid zeros before applying the log transformation. This method helped to shifts all values to positive, making them suitable for log transformation. Also, before applying the log transformation, all negative values were replaced with zero which simplified the log transformation process. Final data analysis was undertaken using Stata 17.0 statistical software.

3.4 Data analytical tools and methods (analytical framework)

3.4.1 Estimating the technical efficiency of maize production in Uganda

The stochastic frontier analysis (SFA) model that was independently formulated by Aigner *et al*. (1977) and Meeusen & Van Den Broeck, (1977) was used in this study. The model is formulated as follows:

The basic form of the SFA model can be expressed as follows:

$Y_i = f(X_i; \beta_i) + V_i - U_i$……………………………………(10)

where;

Y_i is the maize output for the i^{th}farm,

$f(X_i\beta)$is the production function

X_i is a vector of inputs variables (such as., land, labour, fertilizer, maize seeds, manure and pesticides

β represents the parameters to be estimated

V_i is the stochastic error term that captures random noise or statistical variability, assumed to be independently and identically distributed as $N(0, \sigma_v^2)$

u_i is the inefficiency term, representing the shortfall from the frontier, which is non-negative and often assumed to follow a specific distribution, such as exponential or half-normal.

3.4.1.1 Empirical model specification of the Stochastic Production Frontier Model

The Translog production function is a highly suitable choice for Stochastic Frontier Analysis (SFA) in my study due to its flexibility in modeling production relationships. Unlike conventional production functions that assume a specific functional form, the Translog function allows for the estimation of varying elasticities of substitution among inputs. This flexibility is essential in agricultural contexts, where the interaction between inputs can significantly influence output (Önalan & Başeğmez, 2022). Additionally, the Translog function excels in modeling interaction effects among inputs, providing insights into how different factors, such as labor, land, and fertilizers, synergistically influence agricultural output. This is particularly significant in maize production, where input interdependencies can affect productivity outcomes (Mdletshe, 2023).

The model was empirically log linearized to make data more normal or symmetric since a statistical analysis was performed and it assumes normality which log transformation helped to meet the assumption (Jimichi *et al.* 2023). Also, data of all variables was log linearized such that we could interpret the coefficients in terms of percentages.

Therefore, the Translog production function model was log linearized to be:

$$
\begin{aligned}
lnY = \beta_0 + \beta_1 lnx_1 + \beta_2 lnx_2 + \beta_3 lnx_3 + \beta_4 lnx_4 + \beta_5 lnx_5 + \beta_6 lnx_6 \ \ + \beta_7 lnx_7 + 0.5 \\
* \beta_{1_1} \ln(x_1)^2 + 0.5\beta_{2_2} * \ln(x_2)^2 + 0.5\beta_{3_3} * \ln(x_3)^2 + 0.5\beta_{4_4} * \ln(x_4)^2 + 0.5\beta_{5_5} \\
* \ln(x_5)^2 + 0.5\beta_{6_6} * \ln(x_6)^2 + \beta_{1_2}(lnx_1 * lnx_2) + \beta_{1_3}(lnx_1 * lnx_3) \\
+ \beta_{1_4}(lnx_1 * lnx_4) + \beta_{1_5}(lnx_1 * lnx_5) + \beta_{1_6}(lnx_1 * lnx_6) + \beta_{2_3}(lnx_2 * lnx_3) \\
+ \beta_{2_4}(lnx_2 * lnx_4) + \beta_{2_5}(lnx_2 * lnx_5) + \beta_{2_6}(lnx_2 * lnx_6) + \beta_{3_4}(lnx_3 * lnx_4) \\
+ \beta_{3_5}(lnx_3 * lnx_5) + \beta_{3_6}(lnx_3 * lnx_6) + \beta_{4_5}(lnx_4 * lnx_5) + \beta_{4_6}(lnx_4 * lnx_6) \\
+ \beta_{5_6}(lnx_5 * lnx_6) + intercrpe\ share + used\ organic\ fertilizer \\
+ used\ inoraganic\ fertilizer + used\ agricultural\ pesticide \\
+ (v_i - u_i) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots .. (11)
\end{aligned}
$$

where;

In =logarithm to base
Y_i= maize output in the i[th] farmer (kg/ha)
β_{1-6}= coefficients
lnx_1= log land covered by maize (ha)
lnx_2= log quantity of maize seeds used (kg/ha)
lnx_3= log quantity of fertilizer used (kg/ha)
lnx_4= log quantity of manure used (kg/ha)
lnx_5= log quantity of pesticides used (liters)
lnx_6= number of labour (man-days/ha)
Used organic fertilizer- dummy variable

Used inorganic fertilizer- dummy variable

Used agricultural pesticide- dummy variable

Note that to include the panel effect in the stochastic frontier model, the individual-specific effects that account for the unobserved heterogeneity between different entities (such as different farmers or households) was introduced. This is typically done by adding a time-invariant individual effect α_i that captures factors unique to each farmer or unit in the panel. Purposely the model was run by a true randoms effect. Below is how the model was modified to incorporate the panel effect$lnY_{it} = \beta_0 + \beta_1 lnx_{1,it} + \beta_2 lnx_{2,it} + \beta_3 lnx_{3,it} + \beta_4 lnx_{4,it} + \beta_5 lnx_{5,it} + \beta_6 lnx_{6,it} + \beta_7 lnx_7, it + 0.5 * \beta_{1_1} \ln\left(x_{1,it}\right)^2 + 0.5\beta_{2_2} * \ln\left(x_{2,it}\right)^2 + 0.5\beta_{3_3} * \ln\left(x_{3,it}\right)^2 + 0.5\beta_{4_4} * \ln(x_4, it)^2 + 0.5\beta_{5_5} * \ln\left(x_{5,it}\right)^2 + 0.5\beta_{6_6} * \ln\left(x_{6,it}\right)^2 + \beta_{1_2}\left(lnx_{1,it} * lnx_{2,it}\right) + \beta_{1_3}\left(lnx_{1,it} * lnx_{3,it}\right) + \beta_{1_4}\left(lnx_{1,it} * lnx_{4,it}\right) + \beta_{1_5}\left(lnx_{1,it} * lnx_{5,it}\right) + \beta_{1_6}\left(lnx_{1,it} * lnx_{6,it}\right) + \beta_{2_3}\left(lnx_{2,it} * lnx_{3,it}\right) + \beta_{2_4}\left(lnx_{2,it} * lnx_{4,it}\right) + \beta_{2_5}\left(lnx_{2,it} * lnx_{5,it}\right) + \beta_{2_6}\left(lnx_{2,it} * lnx_{6,it}\right) + \beta_{3_4}\left(lnx_{3,it} * lnx_{4,it}\right) + \beta_{3_5}\left(lnx_{3,it} * lnx_{5,it}\right) + \beta_{3_6}\left(lnx_{3,it} * lnx_{6,it}\right) + \beta_{4_5}\left(lnx_{4,it} * lnx_{5,it}\right) + \beta_{4_6}\left(lnx_{4,it} * lnx_{6,it}\right) + \beta_{5_6}\left(lnx_{5,it} * lnx_{6,it}\right) + \alpha_i + intercrop\ share + used\ organic\ fertilizer + used\ inoragnic\ fertilizer + used\ agricultural\ pesticide + (v_{it} - u_{it}) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots..(12)$

where;

Y_{it} is the output for the i^{th} farmer in time period t

$x_{j,it}$ are the inputs for the i^{th} farmer in time t (e.g., labor, land, fertilizer, etc.)

β_j are the parameters to be estimated

α_i represents the unobserved, time-invariant farmer-specific effects (the panel effect)

Intercrop share - which refers to share of plot allocated for maize production and it is measured in hectares.

Used organic fertilizer- dummy variable

Used inorganic fertilizer- dummy variable

Used agricultural pesticide- dummy variable

v_{it} represents random noise (measurement error, external shocks, etc.), which is assumed to be normally distributed.

u_{it} represents the inefficiency term, assumed to follow a truncated normal distribution or half-normal distribution

The panel/time effect in this analysis is explained by the inclusion of:

- Individual-specific random effects (v_i) to account for unobserved heterogeneity across farms.
- Time dummy variables (Period) to capture common trends or shocks affecting all farms over time.
- The error term (u_i) to account for other random disturbances.

These components help to isolate the impact of the independent variables on maize production while controlling for unobserved heterogeneity and time-specific effects.

3.4.1.2 Estimating the elasticity for input variables of the translog production function model

Note that after the model specification and obtaining of coefficiencies for all the variables in the translog production function model, elasticity for each variable was obtained so as to interpret the effect of each input variable on the output. Additionally, during the calculation of elasticity, the mean of the natural logarithm of the variable was multiplied with the corresponding coefficient. Therefore, calculation of elasticity for each input variable was as follows:

3.4.1.3 Elasticity for acreage (land) under maize

$$e_{x1} = \beta_1 + \beta_{1_1} lnx_1 + \beta_{1_2} lnx_2 + \beta_{1_3} lnx_3 + \beta_{1_4} lnx_4 + \beta_{1_5} lnx_5 + \beta_{1_6} lnx_6 \dots \dots \dots \dots \dots \dots . (13)$$

In =logarithm to base.

e_{x1}= elasticity for acreage of maize

$\beta_1 =$ is the coefficient for acreage under maize

β_{1_1}= is the coefficient for acreage under maize squared

$lnx_1 =$is the natural logarithm of acreage under maize

$\beta_{1_2} =$ is the coefficient for the combination of acreage under maize and seed

lnx_2= is the natural logarithm of quantity of seed used

β_{1_3}= is the coefficient for the combination of acreage under maize and quantity of fertilizer

lnx_3= is the natural logarithm of quantity of fertilizer

$\beta_{1_4} =$ is the coefficient for the interaction of acreage under maize and quantity of manure

lnx_4= is the natural logarithm of manure

$\beta_{1_5} =$ is the coefficient for the combination of acreage under maize and quantity of pesticide

$lnx_5 =$ is the natural logarithm of quantity of pesticide

$\beta_{1_6} =$ is the coefficient for the combination of acreage under maize and labour

lnx_6= is the natural logarithm of labour

3.4.1.4 Elasticity for quantity of seed

$$e_2 = \beta_2 + \beta_{2_2} lnx_2 + \beta_{1_2} lnx_1 + \beta_{2_3} lnx_3 + \beta_{2_4} lnx_4 + \beta_{2_5} lnx_5 + \beta_{2_6} lnx_6 \dots \dots \dots \dots \dots \dots \dots . (14)$$

In =logarithm to base.

e_{x2}= elasticity for quantity of seed

$\beta_1 =$ is the coefficient for quantity of seed

β_{2_2}= is the coefficient for quantity of seed squared

$lnx_2 =$is the natural logarithm of quantity of seed

$\beta_{1_2} =$ is the coefficient for the combination of acreage under maize and quantity of seed

lnx_1= is the natural logarithm of acreage under maize

β_{2_3}= is the coefficient for the combination of quantity of seed and quantity of fertilizer

lnx_3= is the natural logarithm of quantity of fertilizer

β_{2_4} = is the coefficient for the interaction of quantity of seed and quantity of manure

lnx_4= is the natural logarithm of quantity of manure

β_{2_5} = is the coefficient for the combination of quantity of seed and quantity of pesticide

lnx_5 = is the natural logarithm of quantity of pesticide

β_{2_6} = is the coefficient for the combination of quantity of seed and labour

lnx_6= is the natural logarithm of labour

3.4.1.5 Elasticity for quantity of fertilizer

$$e_3 = \beta_3 + \beta_{3_3}lnx_3 + \beta_{1_3}lnx_1 + \beta_{2_3}lnx_2 + \beta_{3_4}lnx_4 + \beta_{3_5}lnx_5 + \beta_{3_6}lnx_6 \dots\dots\dots\dots\dots\dots.(15)$$

In =logarithm to base.

e_{x3}= elasticity for quantity of fertilizer

β_3 = is the coefficient for quantity of fertilizer

β_{3_3}= is the coefficient for quantity of fertilizer squared

lnx_3 =is the natural logarithm of quantity of fertilizer

β_{1_3} = is the coefficient for the acreage under maize and quantity of fertilizer

lnx_1= is the natural logarithm of acreage under maize

β_{2_3}= is the coefficient for the combination of quantity of seed and quantity of fertilizer

lnx_2= is the natural logarithm of seed

β_{3_4} = is the coefficient for the interaction of quantity of fertilizer and quantity of manure

lnx_4= natural logarithm of quantity manure

β_{3_5} = is the coefficient for the combination of quantity of fertilizer and quantity of pesticide

lnx_5 = is the natural logarithm of quantity of pesticide

β_{3_6} = is the coefficient for the combination of quantity of fertilizer and labour

lnx_6= is the natural logarithm of labour

3.4.1.6 Elasticity for quantity of manure

$$e_4 = \beta_4 + \beta_{4_4} lnx_4 + \beta_{1_4} lnx_1 + \beta_{2_4} lnx_2 + \beta_{3_4} lnx_3 + \beta_{4_5} lnx_5 + \beta_{4_6} lnx_6 \dots\dots\dots\dots\dots. (16)$$

In =logarithm to base.

e_{x4}= elasticity for quantity of manure

β_4 = is the coefficient for quantity of manure

β_{4_4}= is the coefficient for quantity of manure squared

lnx_4 =is the natural logarithm of quantity of manure

β_{1_4} = is the coefficient for the acreage under maize and quantity of manure

lnx_1= is the natural logarithm of acreage under maize

β_{2_4}= is the coefficient for the combination of quantity of seed and quantity of manure

lnx_2= is the natural logarithm of seed

β_{3_4} = is the coefficient for the interaction of quantity of fertilizer and quantity of manure

lnx_3= is the natural logarithm of quantity of fertilizer

β_{4_5} = is the coefficient for the combination of quantity of manure and quantity of pesticide

lnx_5 = is the natural logarithm of quantity of pesticide

β_{4_6} = is the coefficient for the combination of quantity of manure and labour

lnx_6= is the natural logarithm of labour

3.4.1.7 Elasticity for quantity of pesticide

$$e_5 = \beta_5 + \beta_{5_5} lnx_5 + \beta_{1_5} lnx_1 + \beta_{2_5} lnx_2 + \beta_{3_5} lnx_3 + \beta_{4_5} lnx_4 + \beta_{5_6} lnx_6 \dots\dots\dots\dots\dots (17)$$

In =logarithm to base.

e_{x5}= elasticity for quantity of pesticide

β_5 = is the coefficient for quantity of pesticide

β_{5_5}= is the coefficient for quantity of pesticide squared

lnx_5 =is the natural logarithm of quantity of pesticide

β_{1_5} = is the coefficient for the combination of acreage under maize and quantity of pesticide

lnx_1= is the natural logarithm acreage under maize

β_{2_5}= is the coefficient for the combination of quantity of seed and quantity of pesticide

lnx_2= is the natural logarithm of quantity of seed

β_{3_5} = is the coefficient for the interaction of quantity of fertilizer and quantity of pesticide

lnx_3= is the natural logarithm of quantity of fertilizer

β_{4_5} = is the coefficient for the combination of quantity of manure and quantity of pesticide

lnx_4 = is the natural logarithm of quantity of manure

β_{5_6} = is the coefficient for the combination of quantity of pesticide and labour

lnx_6= is the natural logarithm of labour

3.4.1.8 Elasticity for labour

$$e_6 = \beta_6 + \beta_{6_6} lnx_6 + \beta_{1_6} lnx_1 + \beta_{2_6} lnx_2 + \beta_{3_6} lnx_3 + \beta_{4_6} lnx_4 + \beta_{5_6} lnx_5 \ldots\ldots\ldots\ldots\ldots\ldots.(18)$$

In =logarithm to base.

e_{x6}= elasticity for labour

β_6 = is the coefficient for labor

β_{6_6}= is the coefficient for labour squared

lnx_6 =is the natural logarithm of labour

β_{1_6} = is the coefficient for the combination of acreage under maize and labour

lnx_1= is the natural logarithm of acreage under maize

β_{2_6}= is the coefficient for the combination of quantity of seed and labour

lnx_4= is the natural logarithm of quantity of manure

β_{3_6} = is the coefficient for the interaction of quantity of fertilizer and labour

lnx_3= is the natural logarithm of quantity of fertilizer

β_{4_6} = is the coefficient for the combination of quantity of manure and labour

lnx_4 = is the natural logarithm of quantity of manure

β_{5_6} = is the coefficient for the combination of quantity of pesticide and labour

lnx_5= is the natural logarithm of quantity of pesticide

3.4.2 Estimating the economic efficiency of maize production in Uganda

The economic efficiency of maize production is estimated using a stochastic cost production frontier.it is used by modeling the relationship between cost, input prices, and output, while allowing for inefficiency in cost minimization. This is a parametric approach where random errors and inefficiency terms are included, similarly to the stochastic production frontier.

3.4.2.1 The general form of the stochastic cost frontier function

The stochastic cost frontier can be written as:

Transforming the production function gives us the cost function in general form as;

$C_{ij} = F\left(Y_i, P_{iJ}; \beta\right) + V_i - U_i$ … … … … … … … … … … (19)

where;

C_{ij} is the total cost incurred by ith farm (in your case, a maize farmer),

y_i is the output produced by the farmer,

p_{ij} represents the prices of the inputs used by farmer i^{th} for each input j^{th} (e.g., land, labor, fertilizer),

β are the parameters to be estimated, capturing the impact of output and input prices on cost,

v_i is the random error term capturing statistical noise (assumed to follow a normal distribution with mean zero and variance σ_v^2

u_i is the non-negative cost inefficiency term (usually assumed to follow a truncated normal or half-normal distribution).

The stochastic cost function is suitable for my study due to its ability to separate random errors from inefficiencies, acknowledging that not all deviations from the cost frontier are caused by inefficiency. Some may result from random shocks, measurement errors, or other external factors beyond a farmer's control, such as weather conditions or policy changes. This distinction enhances the precision of efficiency estimates (Aigner, Lovell, & Schmidt, 1977; Kumbhakar & Lovell, 2000). Additionally, the stochastic cost function focuses on cost minimization, which is essential for understanding how well farmers are utilizing inputs relative to their prices. By modeling the cost of production, it helps estimate how close a farmer is to minimizing costs for a given level of output and input prices, which is crucial for determining the cost efficiency of maize farmers (Kumbhakar & Lovell, 2000; Coelli *et al.*, 2005).

3.4.2.2 Empirical model specification

To estimate the economic efficiency, the stochastic cost frontier can be specified using flexible functional forms like the Translog cost function, which allows for variable elasticities of substitution between inputs (Christensen, Jorgenson & Lau, 1973).

Empirically the stochastic cost frontier model can be log linearized. Hence the stochastic frontier translog cost function is stated as;

$$
\begin{aligned}
lnc_i = {} & \beta_0 + \beta_1 ln(w_1) + \beta_2 ln(p_1) + \beta_3 ln(land_i) + \beta_4 ln(y_i) + 0.5 * \beta_{1_1} \ln(w_1)^2 + 0.5 \\
& * \beta_{2_2} \ln(p_1)^2 + 0.5 * \beta_{3_3} \ln(land_i)^2 + 0.5 * \beta_{4_4} \ln(y_i)^2 + \beta_{1_2} ln(w_i) * ln(p_i) \\
& + \beta_{1_3} ln(w_i) * ln(land_i) + \beta_{2_3} ln(p_i) * ln(land_i) + \beta_{4_1} ln(y_i) * ln(w_i) \\
& + \beta_{4_2} ln(y_i) * ln(p_i) + \beta_{4_3} ln(y_i) * ln(land_i) \\
& + \ used\ manure + used\ fertilizer + used\ pesticide + v_i + u_i \text{..........................} (20)
\end{aligned}
$$

where C_i represent the minimum cost of product output y_i, $p_{i1} - p_3$ represent the price of vector inputs and β_0 denotes intercept. v_i is the error component that accounts for stochastic noise effects and u_i is the error component that accounts for the cost inefficiency effect.

$C_i =$ Minimum total cost of maize production (Ug Sh/ha).

β_{1-4} = Coefficients

lnw_i =Wage for labor (Ug Sh/ha).

lnp_i = Price of seed (Ug Sh/ha).

$lnla_i$ = land (ha)

lny_i = Maize output (Ug Sh)

Used manure- dummy variable (1 Yes, 0 otherwise)

Used fertilizer- dummy variable (1 Yes, 0 otherwise)

Used pesticide- dummy variable (1 Yes, 0 otherwise)

$(v_i + u_i)$ = error term

Note that, to include the panel effect in stochastic cost function, the model will be regenerated and analyzed with random effects model as;

$$
\begin{aligned}
lnc_{i,it} = \beta_0 &+ \beta_1 ln(w_{1,it}) + \beta_2 ln(p_{1,it}) + \beta_3 ln(land_i, it) + \beta_4 ln(y_{i,it}) + 0.5 * \beta_{1_1} \ln(w_{1,it})^2 \\
&+ 0.5 * \beta_{2_2} \ln(p_{1,it})^2 + 0.5 * \beta_{3_3} \ln(land_i, it)^2 + 0.5 * \beta_{4_4} \ln(y_{i,it})^2 \\
&+ \beta_{1_2} ln(w_{i,it}) * ln(p_{i,it}) + \beta_{1_3} ln(w_{i,it}) * ln(land_i, it) + \beta_{2_3} ln(p_{i,it}) \\
&* ln(land_{i,it}) + \beta_{4_1} ln(y_{i,it}) * ln(w_{i,it}) + \beta_{4_2} ln(y_{i,it}) * ln(p_i, it) + \beta_{4_3} ln(y_i, it) \\
&* ln(land_i, it) + used\ manure + used\ ferrilizer + used\ pesticide + v_{i,it} \\
&+ u_{i,it} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (21)
\end{aligned}
$$

where;

lnc_i is a dependent variable which represents the natural logarithm of the total cost of producing maize by smallholder farmer *i* at time *t.* Taking the logarithm helps normalize the data, allowing for interpretation of the coefficients in terms of percentage changes.

$ln(w_{1,it})$ represents the natural logarithm of the wage rate paid to labor for farmer *i* at time *t*. This variable assesses how changes in labor costs affect the total cost of maize production. Higher wage rates can lead to increased production costs.

$\beta_2 ln(p_{1,it})$ represents the natural logarithm of the price of inputs (such as seeds, fertilizers, etc.) used by farmer *i* at time *t*. This captures how fluctuations in input prices influence the overall cost of producing maize.

$ln(land_i, it)$ This variable represents the natural logarithm of the land area used for maize production by farmer *i* at time *t*.

$ln(y_{i,it})$ The natural logarithm of the yield (output) of maize produced by farmer *i* at time *t*. This variable reflects the relationship between production output and costs. Higher yields may imply economies of scale, affecting cost per unit.

$0.5 * \beta_{1_1} \ln(w_{1,it})^2$ this represents a square term of wages. This term captures the quadratic effect of wage rates on production costs, allowing for the possibility that the impact of wages on costs may not be linear. It assesses if increasing wage rates have diminishing or increasing returns on cost.

$0.5 * \beta_{2_2} \ln(p_{1,it})^2$ Similar to the previous term, this captures the non-linear relationship between input prices and costs, indicating how changes in input prices impact the total cost of production at different levels.

$0.5 * \beta_{3_3} \ln(land_i, it)^2$ is an interaction term representing the effect of the square of the natural logarithm of the land area used for maize production by farmer *i* at time *t*.

$\ln(y_{i,it})^2$ This quadratic term assesses the non-linear relationship between maize yields and costs, indicating how varying output levels influence total production costs.

$ln(w_{i,it})ln(p_{i,it})$This interaction term assesses how the relationship between labor costs and total production costs varies with changes in input prices. It indicates the joint effect of labor and input prices on production costs.

$ln(y_{i,it})ln(w_{i,it})$ This interaction explores how the relationship between maize yields and production costs is influenced by labor costs, indicating if higher yields offset increased labor costs.

$ln(y_{i,it})ln(p_i, it)$This term examines the interaction between maize yields and input prices, assessing how higher output may mitigate or exacerbate the effects of input price changes on production costs.

Used fertilizer-dummy variable (1 Yes, 0 otherwise)

Used pesticide- dummy variable (1 Yes, 0 otherwise)

Used manure- dummy variable (1 Yes, 0 otherwise)

$v_{i,it}$ This represents the individual-specific effects that account for unobserved heterogeneity among smallholder farmers that may impact their production costs.

$u_{i,it}$ represents the inefficiency term.

Note that, the model specified above represents a functional form used to analyze the relationship between a dependent variable $c_{i,it}$ and several independent variables, where the subscripts i and *t* indicate individual (or entity) and time dimensions, respectively. This is common in panel data analysis.

The purpose of this model is that, this econometric model is designed to estimate how changes in independent variables, such as wages, prices, labor, and output, influence the dependent variable $c_{i,it}$while accounting for both individual-specific and time-specific effects. By incorporating a panel data structure, which includes both entity (*i*) and time (*t*) dimensions, the model leverages the advantages of panel data analysis. This approach allows for better control of unobserved heterogeneity, as it can account for individual characteristics that do not change over time, thus improving estimation efficiency. Ultimately, the model aims to provide a comprehensive understanding of the dynamics influencing total costs in maize production among smallholder farmers in Uganda, facilitating more accurate policy recommendations and insights into agricultural economics.

3.4.2.3 Estimating the elasticity for variables in the economic efficiency model

Note that after the translog cost function model specification, elasticity of variables in the model were obtained to predict the effect of each variable on the total cost of producing maize. Below is the calculation of elasticity for each variable in the cost function. Like for the translog production function, elasticity was calculated by multiplying the mean of the natural logarithm of the variable with it is corresponding coefficient. Therefore, calculation of elasticity for each cost function variable was as follows:

3.4.2.4 Elasticity for wage rate

$$ew_i = \beta_1 + \beta_{1_1} lnw_i + \beta_{1_2} lnp_i + \beta_{1_3} lnla_i + \beta_{4_1} lny_i \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.(22)$$

where;

ew_i = Represents the elasticity for wage rate

β_1= represents the coefficient of wage rate

β_{1_1} = represents the coefficient of wage rate squared

lnw_i = is the natural logarithm of wage rate

β_{1_2} =represents the coefficient for the combination of wage rate and price of seed

lnp_i= is the natural logarithm of price of seed

β_{1_3}= is the coefficient for the combination of wage rate and land under maize

$lnla_i$ = is the natural logarithm of land

β_{4_1}= is the coefficient for the combination of maize output and wage rate

lny_i= is the natural logarithm of maize output.

3.4.2.5 Elasticity for price of seed

$$ep_i = \beta_2 + \beta_{2_2} lnp_i + \beta_{1_2} lnw_i + \beta_{2_3} lnla_i + \beta_{4_2} lny_i \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots . (23)$$

where;
ep_i = Represents the elasticity for price of seed

β_2= represents the coefficient of price of seed

β_{2_2} = represents the coefficient of price of seed squared

lnp_i = is the natural logarithm of price of seed

β_{1_2} =represents the coefficient for the combination of wage rate and price of seed

lnw_i= is the natural logarithm of wage rate

β_{2_3}= is the coefficient for the combination of price of seed and land under maize

$lnla_i$ = is the natural logarithm of land

β_{4_2}= is the coefficient for the combination of maize output and price of seed

lny_i= is the natural logarithm of maize output

3.4.2.6 Elasticity for land area under maize

$$eland_i = \beta_3 + \beta_{3_3} lnla_i + \beta_{1_3} lnw_i + \beta_{2_3} lnp_i + \beta_{4_3} lny_i \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots..\ldots\ldots.(24)$$

where;

$eland_i$ =Represents the elasticity land area under maize

β_3= represents the coefficient of land area under maize

β_{3_3} = represents the coefficient of land area under maize squared

$lnla_i$ = is the natural logarithm of land area under maize

β_{1_3} =represents the coefficient for the combination of wage rate and land area under maize

lnw_i= is the natural logarithm of wage rate

β_{2_3}= is the coefficient for the combination of price of seed and land under maize

lnp_i = is the natural logarithm of price of seed

β_{4_3}= is the coefficient for the combination of maize output and land area under maize

lny_i= is the natural logarithm of maize output

3.4.2.7 Elasticity maize output

$$ey_i = \beta_4 + \beta_{4_4} lny_i + \beta_{4_1} lnw_i + \beta_{4_2} lnp_i + \beta_{4_3} lnland_i \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.(25)$$

where;

ey_i =Represents the elasticity land maize output

β_4= represents the coefficient of maize output

β_{4_4} = represents the coefficient of maize output squared

lny_i = is the natural logarithm of maize output

β_{4_1} =represents the coefficient for the combination of maize output and wage rate

lnw_i= is the natural logarithm of wage rate

β_{4_2}= is the coefficient for the combination of maize output and price of seed

lnp_i = is the natural logarithm of price of seed

β_{4_3}= is the coefficient for the combination of maize output and land area under maize

$lnland_i$= is the natural logarithm of land area under maize

3.4.3 Determinants of technical and economic efficiency of maize production

To examine the factors affecting the technical and economic efficiency of smallholder maize farmers in Uganda, the study utilized the Random effects Tobit model. This model is particularly appropriate for this research because the dependent variable (efficiency scores) is censored or restricted within a specific range (between 0 and 1). Additionally, Random effects Tobit models are efficient and flexible, making them especially suitable for analyzing large datasets like panel data. The same model was applied in studies by Abdulai and Huffman (2000).

Theoretically, the Tobit model can be specified as;

$$Y^* = \beta_o + \sum_{n=1}^{15} \beta_n X_i + \varepsilon_i \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots.. (26)$$

where

Y*= efficiency scores

β_0= constant

X_1= gender of household head (male = 1, female = 0)

X_2= distance travelled by a smallholder maize farmer from the farm/ household to reach agricultural extension services (kilometers)

X_3= intercrop share (hectares)

X_4= distance travelled by a smallholder maize farmer from the farm/ household to access the bank (kilometers)

X_5= distance travelled by a smallholder maize farmer from the farm to access agricultural input market (kilometers)

X_6= distance travelled by a smallholder maize farmer from the farm to access feeder road (kilometers)

X_7= distance travelled by a smallholder maize farmer from the farm/ household to the murrum trunk (kilometers)

X_8= distance travelled by a smallholder maize farmer from the farm to the tarmac road (kilometers)

X_9= age of household head (years)

X_{10}= age of household head square (years)

X_{11}= household size (number of persons)

X_{12}= education (number of schooling years)

β_n = unknown parameters that are estimated through econometric modeling.

ε_i= error term

To incorporate the panel effect in the model, the model was analyzed by use of true randoms effects model.

Therefore, the Tobit model was then regenerated as;

$$Y_{it}^* = \beta_o + \sum_{n=1}^{15} \beta_n X_{itn} + \alpha_i + \tau_t + \varepsilon_{it} \dots\dots\dots\dots\dots\dots\dots. (27)$$

where;

Y_{it}^* is the latent dependent variable representing technical or economic efficiency of maize farmers. It is unobserved but can be measured indirectly, for example, through efficiency scores.

β_o is the intercept of the model

β_n is the Coefficients showing the impact of each independent variable on the dependent variable.

X_{itn} are the independent variables (factors) hypothesized to influence technical or economic efficiency. These may include; distance travelled by smallholder maize farmers to the market, access to credit, age of household head, gender of household head, household size**,** level of education among others

α_i are Individual-specific effects capturing unobserved factors related to each farmer.

τ_t are time-specific effects capturing factors that change over time and affect all individuals

ε_{it} is the error term accounting for random noise or unobserved variables that change over both time and individuals.

Note that the unit of analysis was at household level where plot level data was collapsed to household level.

For example, I calculated the average (mean) age (in years) of all plot managers within the same household and aggregated the data at the household level. Gender was recorded as a binary variable, where males were coded as 1 and females as 0. At the household level, it was expressed as the proportion of males.

Age of plot manager; This meant the length of time that a person existed since birth and it was measured in years. During analysis, the unit of measurement of this variable was at household level. The researcher got average for age (years) of all plot managers within the same household and collapsed the data at household level.

The average for age (years) of all plot managers within the same household was collapsed to get one single variable at household level.

Education of plot manager: This variable refers to the number of schooling years that the plot manager spends in formal education. This variable is used as a proxy variable for the managerial ability in decision making, resource allocation and adaptability. It is assumed that through education a farmer can be in position in using the available resources efficiently and adapt to improved technology easily compared to uneducated farmers who are sometimes conservative (Farah & Amara, 2023). The unit of measurement for this variable was at household level, where the researcher aggregated plot level data to the household level. for this variable, the researcher got average for the number of schooling years for all plot managers with in the same household and collapsed the data to household level.

Gender of plot manager; Gender was considered as sex and was measured as a binary variable, with males coded as 1 and females coded as 0. However, it was treated as proportion of male at household level.

3.5 Definition of variables and summary statistics

Table 1: Variable in The Stochastic Production Function Frontier Model

Variable (x_i)	**Definition of the variable**	**Measurement units**	**Summary statistics**		**Expected sign/direction**
			Mean	SD	
Maize output	This is the dependent variable of the production function. It is the physical quantity of maize output	Kg	348.41	821.54	
Land	Represents the physical unit of land allocated for maize production	Ha	1.037	2.13	+
Seed	This represents the quantity of maize seed used in the production of maize.	Kg ha^{-1}	7.27	10.84	+
Fertilizer	Represents the quantity of fertilizer used by the	Kg ha^{-1}	0.96	11.24	+

	sample household for maize production.				
manure	Manure represents the quantity of manure used in maize production	Kg ha^{-1}	13.146	165.31	+
Pesticide	Pesticide represents the quantity of pesticides used by maize farmers during maize production.	Liters ha^{-1}	0.533	11.79	+
Ln labor	This represents both family and hired laborers	Man-days (ha^{-1})	57.71	49.38	+/-

Table 2: Variable in the stochastic cost function frontier model

Variable, (pi in Ug shillings)	**Definition of the variable**	**Measurement units**	**Summary statistics**		**Expected sign/direction**
			Mean	SD	
Total production cost	Cost of production	UG shillings	27098.98	98614.97	
Maize output	It is the physical quantity of maize output	Kg ha^{-1}	348.41	821.54	+
Land	Represents the physical unit of land allocated for maize production	Ha	1.037	2.13	+
Wage	Average price payed to man power	UG shillings	6355.17	3408.80	+
Seed price	Average price of maize seed	UG shillings	2771.81	3088.92	+

Table 3: Variables affecting technical and economic efficiency

Variable, (x_i	**Definition of the variable**	**Measurement units**	**Summary statistics**		**Expected sign/direction**
			Mean	SD	
TE and EE efficiency score	Score from zero to one				
Gender of household head	The gender of maize farmers was measured as a binary variable, with males coded as 1 and females coded as 0. This classification allowed the analysis to treat gender as a representation of biological sex.	sex.	0.67	0.47	+/_

Distance to agricultural extension staff	This variable represents the distance traveled by maize farmers from their homes to access agricultural extension staff. And was measured in kilometers.		7.81	8.47	-
Distance to the bank;	This variable represents the distance traveled by maize farmers from their homes to reach the bank	measured in kilometers.	22.80	21.88	-
Distance to agricultural input markets	This variable represents the distance traveled by maize farmers from their homes to the input markets and was measured in kilometers.	measured in kilometers.	8.19	9.13	-
Distance to feeder road	This variable represents the proximity of distance from maize farms to the feeder road in	kilometers.	1.83	3.12	-
Distance to tarmac road	This variable represents the distance from maize farms to the tarmac road	kilometers	18.35	16.32	-
Distance to marrum trunk	This variable represents the distance from maize farms to the marrum trunk	kilometers.	7.71	12.50	-
Household size	This variable represents the total number of people in the household	Number of persons	4.77	2.93	+/-
Age of household	This refers to the age of the household	Years	46.89	15.27	+/-
Education	Number of schooling years	Numbers of schooling years	6.32	4.24	+/_

CHAPTER FOUR
RESULTS AND DISCUSSION

4.1 Estimating the technical efficiency of maize production in Uganda

Table 4 presents the Translog production function results for maize production in Uganda, based on secondary data from the Uganda National Panel Survey (UNPS) for the period 2013/2014 to 2019/2020, with a sample size of 8,030 observations. The table includes coefficients, standard errors, and p-values for each variable, providing insights into their statistical significance and effect sizes. Key independent variables include measures of land, seed, fertilizer, manure, pesticide, and labor, along with their squared terms and interaction effects. Additionally, the analysis considers dummy variables for fertilizer and pesticide use, intercrop share, and a time period effect. The table 1 also reports the overall model fit statistics, including Wald chi-square values and number of observations, to assess the robustness and significance of the findings. The coefficients from the translog production function were used to compute elasticities of inputs with respect to output. The elasticities are presented in table 5

Table 4: Translog production function results for maize production in Uganda

Independent variables	Coefficient	Standard error.	p-value
Ln land	0.514***	0.084	0.000
Ln seed	0.326***	0.069	0.000
Ln fertilizer	-0.210	0.164	0.200
Ln manure	0.038	0.190	0.841
Ln pesticide	0.004	0.056	0.946
Ln labor	0.016	0.087	0.853
(Ln fertilizer)2	0.105***	0.039	0.007
(Ln land)2	0.013	0.026	0.633
(Ln seed)2	0.025	0.022	0.260
(Ln manure)2	0.022	0.036	0.545
(Ln pesticide)2	0.016	0.019	0.402
(Ln labor)2	0.038*	0.023	0.103
Ln (land)*Ln(seed)	0.052***	0.019	0.006
Ln (land)*Ln(fertilizer)	-0.116***	0.039	0.003
Ln (land)*Ln(manure)	-0.004	0.014	0.796
Ln (land)*Ln(pesticide)	0.016	0.031	0.615
Ln (land)*Ln(labour)	-0.053***	0.020	0.008
Ln (seed)*Ln(fertilizer)	0.097***	0.029	0.001
Ln (seed)*Ln(manure)	-0.002	0.010	0.828
Ln (seed)*Ln(pesticide)	0.009	0.026	0.717
Ln (seed)*Ln (labour)	-0.001	0.017	0.972
Ln (fertilizer)*Ln(manure)	0.009	0.011	0.392
Ln (fertilizer)*Ln(pesticide)	-0.014	0.016	0.365
Ln (fertilizer)*Ln (labour)	-0.028	0.031	0.379
Ln (manure)*Ln (pesticide)	0.015*	0.010	0.135
Ln(manure)*Ln (labour)	-0.027**	0.014	0.052
Intercrop share	0.599***	0.037	0.000
used organic fertilizer (rev-dummy)	0.023	0.404	0.955
used inorganic fertilizer (rev-dummy)	-0.230**	0.090	0.011
used ag pesticide(rev-dummy)	-0.081**	0.040	0.043
Period	0.089***	0.018	0.000
Cons	4.828***	0.449	0.000
Sigma_u	0.657***	0.017	0.000
Signa_v	0.596***	0.013	0.000
Lambda	1.102***	0.027	0.000
Wald chi2(31) = 5183.11			
Number of observations(n)=8030			

Source: UNPS secondary data by UBOS for the period 2013/2014 up to 2019/2020

Note: the asterisks indicate levels of significance. where* significance levels at 10%, ** is significant at 5% and *** is significant at 1%

4.1.1 Elasticities of determinants of maize output in Uganda

Table 5 indicates that, the mean quantity of maize seed used is 7.27 Kg/ha, with a standard deviation of 10.84 Kg/ha. The elasticity of 0.347 implies that a 1% increase in seed usage is associated with a 0.35% increase in maize output, demonstrating the importance of seed quantity for productivity. The finding is line with the finding by Akinyemi et al. (2020) who also found that farmers who increased their seed rates by 10% saw a 15-25% increase in maize yields, indicating that seed quantity has a direct and substantial effect on output.

Farmers allocated an average of 1.037 hectares of land to maize production, with a standard deviation of 2.13 hectares. With an elasticity of 0.370, a 1% increase in land is associated with a 0.37% increase in maize output, suggesting land positively influences productivity. The finding aligns with the finding of Kibirige (2014), who reported that increased land area significantly influenced maize output in Masindi District, Uganda. other studies, by Kanyenji et al. (2021), also, found that larger farm sizes dedicated to maize production enhance both productivity and technical efficiency in sub-Saharan Africa. Additionally, Gaya et al. (2022) found that land expansion, coupled with improved management practices, significantly increased maize yields in rural Kenya, emphasizing the importance of land as a key input in agricultural systems.

Fertilizer (Kg ha^{-1}): The mean fertilizer application is 0.96 Kg/ha, with a high standard deviation of 11.24 Kg/ha, highlighting significant disparities in fertilizer use. Despite its expected positive effect, elasticity is negative (-0.118), suggesting inefficiencies in fertilizer application. Studies by Bekunda et al. (2020) also found that farmers applying insufficient fertilizer (such as rates below recommended levels) had poor maize yields, often due to nutrient deficiencies that led to lower productivity.

Manure (Kg ha^{-1}): On average, farmers applied 13.146 Kg/ha of manure, with a large variation (standard deviation: 165.31 Kg/ha). Although expected to improve soil fertility, its elasticity is slightly negative (-0.068), potentially due to limited availability. The results are in line with the finding of Vanlauwe et al. (2019) who found that suboptimal manure application, especially when the amount is too low, may not lead to significant increases in crop yield. This study was conducted in sub-Saharan Africa in maize production

Pesticide (Liters ha^{-1}): Farmers used an average of 0.533 Liters/ha of pesticide, with a standard deviation of 11.79 Liters/ha. While pesticides aim to reduce pest-related losses, the elasticity is negative (-0.092), indicating possible misapplication. The findings are in line with the results by Saharan et al. (2020) who fund that under-application of pesticides led to insufficient pest control, contributing to long-term damage to maize crops. The study was conducted in West Africa.

Labor (Man-days ha^{-1}): Labor input, including both family and hired labor, averages 57.71 man-days/ha with a standard deviation of 49.38 man-days/ha. The elasticity of 0.434 suggests that a 1% increase in labor input is associated with a 0.43% increase in maize output, indicating a strong positive association when labor is effectively utilized. However, excess labor may lead to inefficiencies, as shown by the possible +/- direction. Research by Munyua et al. (2021) also found that an increase in labor input was positively correlated with improved maize yields, particularly in areas where labor was used for timely planting, weeding, and pest control. The study focus looked at small holder farmers in Kenya.

Table 5: Elasticities of determinants of maize output in Uganda

Independent variables lny_i	Elasticity	Mean
Ln land	0.370	1.037
Ln quantity seed	0.347	7.27
Ln quantity fertilizer	-0.118	0.96
Ln quantity manure	-0.068	13.146
Ln quantity pesticide	-0.092	0.533
Ln labor	0.434	57.71

Source: UNPS secondary data by UBOS for the period 2013/2014 up to 2019/2020

4.2 Estimating the economic efficiency of maize production in Uganda

Table 6 presents the results of a translog cost function analysis for production in Uganda, using data from the Uganda National Panel Survey (UNPS) covering the period 2013/2014 to 2019/2020. This table shows the estimated coefficients, standard errors, and p-values for various input prices (such as wages, land, seed prices, and maize output as the independent variables). And the total cost as the dependent variable. The coefficients of the prices and output were used to compute elasticities of prices with respect to cost and are presented in table 7

Table 6: Translog cost function results for maize output at household level in Uganda

Independent variables	Coefficients	Standard error	p-Value
Ln wage	0.763***	0.115	0.000
Ln land	0.502**	0.227	0.040
Ln seed price	-0.023**	0.098	0.020
Ln maize output	0.685***	0.129	0.000
(Ln wage)^2	-0.124***	0.023	0.000
(Ln land)^2	0.039	0.068	0.210
(Ln seed price)^2	-0.170***	0.022	0.000
(Ln maize output)^2	-0.000	0.023	0.984
Ln (seed price) *Ln(wage)	-0.022***	0.004	0.000
Ln (seed price) *Ln(land)	-0.055***	0.013	0.000
Ln (wage)*Ln (land)	0.018	0.016	0. 279
Ln (maize output) *Ln (seed price)	0.017	0.007	0.155
Ln (maize output) *Ln (wage)	0.028	0.009	0.072
Ln (maize output) *Ln(land)	0.045	0.031	0.139
Used manure (1=yes)	1.082	0.313	0.501
Used fertilizer (1=yes)	2.750	0.320	0.000

Used pesticide (1=yes)	25.197	0.205	0.000
Period	0.464***	0.115	0.000
$(\text{Period})^2$	-0.034***	0.007	0.000
Ln (wage) *Ln (period)	-0.046***	0.006	0.000
Ln (land) *Ln (period)	-0.112***	0.019	0.000
Ln (seed price) *Ln (period)	-0.0142***	0.004	0.000
Ln (maize output) *Ln (period)	-0.108	0.012	0.000
Constant	-8.592***	0.920	0.000
Wald chi2(18)= 2776.40			
Number of observations(n)=8376			

Source: UNPS secondary data by UBOS for the period 2013/2014 up to 2019/2020

Note: the asterisks indicate levels of significance. Where* significance levels at 10%, ** is significant at5% and *** is significant at 1%

4.2.1 Elasticities of determinants of maize production costs in Uganda

Table 7 results indicate that, the mean output of maize is 348.41 kg/ha, with a standard deviation of 821.54 kg/ha. The elasticity of 0.228 indicates that a 1% increase in maize output leads to a 0.23% increase in total production costs. This positive relationship is expected, as achieving higher output requires additional inputs such as fertilizers, labor, and seeds, driving up overall costs.

Land was significant and positive implying that, a 1% increase in the amount of land used leads to a 0.502% increase in production costs. The positive elasticity shows that as farmers use more land, costs rise, possibly due to the increased need for labor and other inputs. This result aligns with findings by Muyanga & Jayne (2019), who observed that expanding farm size in Kenya's maize production increased total output and, consequently, the overall cost of production due to higher input requirements (e.g., labor and seed).

The average wage paid to labor is 6,355.17 UGX, with a standard deviation of 3,408.80 UGX. The elasticity of -0.368 suggests that a 1% increase in wages reduces total production costs by 0.37%. This counterintuitive result might be explained by higher wages attracting more skilled or efficient labor, leading to improved productivity and cost savings in other inputs.

The mean seed price is 2,771.81 UGX, with a standard deviation of 3,088.92 UGX. The elasticity of -0.046 indicates that a 1% increase in seed prices results in a minimal 0.05% reduction in total costs. The higher price reflects use of improved seed that is associated with higher yield thus reducing the cost of a unit output of maize

Table 7: Elasticities of determinants of maize production costs in Uganda

Independent variables	Elasticity	Mean
lnwage_i	-0.368	6,355.17
lnprice of seed_i	-0.046	2,771.81
lnland_i	0.177	1.037
lnmaize output_i	0.228	348.41

Source: UNPS secondary data by UBOS for the period 2013/2014 up to 2019/2020

4.3 Factors affecting technical and economic efficiency of maize farmers in Uganda

Table 8 below presents the Tobit estimation results of equation (22) on the factors affecting the technical and economic efficiency of maize farmers in Uganda. The results revealed that, among the factors which affected technical efficiency included;

Distance travelled by the smallholder maize farmers from their households/farms to feeder roads was associated with increase in technical efficiency by 0.01% at 5% significance level. This is because closer proximity to roads provides easier access to input and output markets, extension services and other essential agricultural resources, all of which positively affect productivity and efficiency. Supporting research by Dorsis (2022) found that farmers located closer to all-weather roads were able to access markets more easily, leading to higher productivity levels. The study highlighted that proximity to roads facilitates timely access to markets for selling produce and acquiring inputs, ultimately enhancing technical efficiency.

Age of household head was associated with a reduction in technical efficiency by 0.2%. This could be attributed to the fact that older farmers are less energetic and weakly adapt to improved technology due to conservativeness compared to young energetic farmers. In addition, research by Adeagbo et al. (2023) also found that younger farmers are generally more open to learning and adapting to new practices, enhancing their technical efficiency. In contrast, older farmers may struggle to change their established routines, which limits their ability to optimize production processes and resources effectively.

Household size was positively associated with maize farmers' technical efficiency at 1% level. Having an additional member in the household was associated with an increase in technical efficiency by 0.7%. This implies that there is a statistically significant relationship between the number of members in a household and the technical efficiency of maize farmers. The positive coefficient for household size means that as the number of household members increases, the technical efficiency of maize farming also increases. The results are in line with findings of Kamau, (2015), Ayinde et al., (2015), Ahmed et al., (2015) and Kibirige, (2014) who explained that, as household members increase there will be a guarantee of availability of family labor for farm operations to be accomplished in time. For example, during the peak of the seasons, there is a shortage of labour and hence a household with large family size would deploy more labor to undertake the necessary farming activities like ploughing, weeding and harvesting on time than their counterparts hence becoming more efficient in production.

Education had a significant positive and was associated with an increase in technical efficiency at 1% level. Having formal education by a plot manager was associated with increase in technical efficiency by 0.3 %. Education equips farmers with essential knowledge and skills that enable them to make informed decisions about crop management, pest control, and resource allocation.

Studies have shown that educated farmers are better able to implement modern agricultural practices and technologies, which can significantly enhance technical efficiency (Paltasingh & Goyari, 2018). Also, such influence was also reported by Mburu et al., (2014), Thabethe & Mungatana (2014), Mutoko et al., (2015) and Bati et al., (2017). The authors explained that farmers with formal education are able to acquire, analyze and comprehend important information about input mix and better production practices, better manage their farm resources and other agricultural activities all of which increase their ability to make timely decisions during production than uneducated ones.

Whereas factors which affected economic efficiency included;

Gender of household head was significant at 1% and increased economic efficiency by 0.7 %. This implies that male heads of households have higher management competences and have fewer constraints in terms of finding labour in their activities of agricultural production. Additionally, women are generally less capable than men of being guaranteed land rights or having more access to land. These rigidities in terms of land rights and labour in the household or in the community, together with the high control typically exerted by men could be contributing to women's low economic efficiency. A study by Mehare & Bekele (2023) found that male-headed households in sub-Saharan Africa tend to have higher productivity and economic efficiency in agricultural production than female-headed households. This is often attributed to greater access to productive resources like land, inputs, and extension services for men. A contradicting study Awal, (2017) who found a negative relationship of economic efficiency with gender where male headed household of maize farmers in Ghana were not economically efficient.

Distances travelled by smallholder maize farmers from their households/farms to access agricultural extension services by extension workers reduces economic efficiency. An additional kilometer between maize- farming households and extension service providers were associated with lowering the economic efficiency by 0.1 % at 1% significance level. Agricultural extension services provide farmers with essential information on the latest farming techniques, pest management, soil health, and crop rotation practices. This knowledge helps farmers to improve their farming practices, leading to increased productivity and economic efficiency. Farmers further away from extension services may have less frequent interactions with extension officers, limiting their access to vital information, support and increased distances can delay the adoption of new technologies and practices, as farmers might not receive timely updates and training. The findings are in line with the results of Osman, et al. (2018).

Distance travelled by smallholder maize farmers from their farms/households to murrum trunk had negative association with economic efficiency at 1% significance level. A 1% increase in distance form smallholder maize farm to marrum trunk by one kilometer decreased economic efficiency level by 0.1%. The negative coefficient implies that as the distance to murrum trunk roads increases, the economic efficiency of maize farmers decreases. This suggests that proximity to these roads is crucial for maintaining or improving economic efficiency. Murrum trunk roads, typically unpaved but essential rural roads, play a critical role in the transportation of goods and people. They provide vital links between farming areas and markets, storage facilities, and service centers. Increased distances to these roads mean higher transportation costs and longer travel times for farmers. The results are in line with findings of Okwera, (2021) who found a negative relationship between economic efficiency and distances to main road of smallholder maize and rice farmers in Amuru and Nwoya districts of Northern Uganda.

The age of the household head was strongly associated with a positive economic efficiency by 0.3 % at 1% significance level. this can be partly attributed to the fact that; young farmers can be economically efficient than older farmers. A study by Djuraeva, et al. (2023) found that in Uzbekistan, younger farmers displayed higher economic efficiency compared to older farmers due to their greater openness to adopting modern technologies and farming practices. The study revealed that younger farmers were more likely to embrace innovations, which improved their resource use and reduced costs.

The squared age of the household head had a negative association with economic efficiency at 1% significance level. As farmers age go up their level of economic efficiency is reduced by -0.00003%. This could be attributed to reduced energies, and the conservative nature of the aged farmers which makes it difficult for them to accept new agricultural technologies and innovations such as use of improved seeds, fertilizer use, mechanization, among others, thereby preventing such farmers from operating on higher production frontiers. It could also be lower energies of the older farmers, which demotivates them from adopting the technologies hence becoming less economically efficient. The results are in line with Li et al. (2021) who studied the impact of age on the economic efficiency of farmers in rural China. They reported that while older farmers initially benefit from experience, their efficiency begins to decline after a certain age due to factors such as reduced physical capacity and reluctance to adopt new farming practices.

The result showing that household size has a negative association with economic efficiency, with a coefficient of 0.2% at a 1% significance level, indicates that as the number of household members increases, the economic efficiency of maize farmers decreases by 0.2%. This suggests that larger households are less efficient in their maize farming operations, likely due to increased consumption pressure, resource misallocation, or inefficiencies in labor utilization. Murunga

(2024) analyzed the relationship between household size and farm productivity in smallholder farms in Kenya. Their study showed that larger households tend to have more consumption needs, which reduces the capital available for productive investment, thereby reducing farm efficiency. Belet et al., (2014) also had similar findings, and their argument was based on the fact that large household size increases the population pressure on the farmer's limited resources due to increases in household spending.

Education was significant at 1% significance level and reduced economic efficiency by 0.5%. This implies that, more educated farmers are less economically efficient than uneducated ones. Highly educated farmers are often engaged in off-farm economic activities reducing their time allocation to their farm business rendering them to be economically inefficient. The results are in line with findings of Mwalupaso et al. (2019) who found that in rural Zambia, farmers with higher education levels were less efficient in maize production because they were more likely to engage in non-farm income-generating activities, such as small businesses, which distracted from managing their farms efficiently. However, these results contradict with findings of Kamau (2015), Sisay et al., 2017 and Mustefa (2017) who found positive relationship of economic efficiency with education level of a farmer in maize production.

Table 8: Tobit regression estimates of factors affecting maize technical and economic efficiency of maize farmers in Uganda

Dependent variable	**Technical efficiency**		**Economic efficiency**	
Independent variables	Coefficient	Std.Err	Coefficient	Std.Err
Gender of household head (sex)	-0.00409	0.006	0.00685***	0.0038293
Distance to the agricultural extension service (km)	0.00009	0.000	-0.00097***	0.000
Distance to the bank (k)	-0.00018	0.000	0.00049***	0.000
Distance to the agricultural in-put markets (km)	-0.00016	0.000	-0.00072	0.000
Distance to the feeder roads (km)	0.00139**	0.000	0.00029***	0.001

Distance to the tarmac road (km)	0.00001	0.000	-0.00041***	0.000
Distance to the marrum trank (km)	0.00013	0.000	-0.00112***	0.000
Age of the household head (years)	-0.00184*	0.001	0.00321***	0.001
Age of the household head squared (years)	0.00002	0.000	-0.00003***	6.54e-06
Household size (number of household members)	0.00709***	0.001	-0.01558***	0.001
Education (number of years in school)	0.00306***	0.001	-0.00480***	0.001
Constant	0.58400***	0.0261	0.31402***	0.022
N=7,951				

Source: Source: UNPS secondary data by UBOS for the period 2013/2014 up to 2019/2020

4.4: Efficiency scores of maize farmers in Uganda

The efficiency scores for maize farmers in Uganda, presented in Table 9, highlight the performance of smallholder farmers in terms of both technical efficiency (TE) and economic efficiency (EE). The results show that, on average, the technical efficiency of the sample households was 56.7%, indicating that farmers could potentially increase their maize production by up to 43.3% without needing to invest additional resources if they were able to fully optimize the use of their inputs. Whereas, the mean economic efficiency was 9.6%. farmers can still reduce input costs by up to 90.4% while maintaining the same output. Alternatively, they could increase output by 90.4% while keeping input costs and technology unchanged.

Table 9: Summary statistics of efficiency score of maize farmers in Uganda

Type of efficiency	**Mean in percentage**	**Standard deviation**	**Minimum**	**Maximum**
TE	56.7%	0.18	0.001	0.911
EE	9.6%	0.10	0.001	0.752

Source: UNPS secondary data by UBOS for the period 2013/2014 up to 2019/2020

CHAPTER FIVE

CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusions

Basing on the findings from the results, the study concludes that

1. Smallholder maize framers in Uganda are technically inefficient accepting the null hypothesis
2. Smallholder farmers in Uganda are economically inefficient accepting the null hypothesis
3. A random effects Tobit model revealed that factors such as distance by maize farmers from their households to access feeder roads had a significant positive effect on technical efficiency thus rejected the null
4. Distance to extension services had a significant negative impact on economic efficiency thus accepting the null
5. Level of education among smallholder maize farmers also had a significant negative effect on economic efficiency accepting the null hypothesis.

5.2 Recommendation

Based on the study's findings, the study recommends improvement in road access, investment in education and strengthening extension services.

5.3 Study limitations

Secondary data often requires significant data cleaning and regression imputation issues. Issues may include bias or distortion of the outcome of the results.

5.4 Suggestions for Further Research

The current study assesses the technical and overall economic efficiency of farmers in maize production in Uganda using Uganda National panel Survey data. Further studies may focus on allocative efficiency in maize production in Uganda to determine whether specific resources are over utilized or under-utilized.

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APPENDICES

Appendix 1: Map of the Major Maize Growing Districts