

# Technical Efficiency and Small Scale Maize Producers in Mwanza Region: A Stochastic Frontier Analysis

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**ABSTRACT**--- This study measured technical efficiency and its determinants in maize production by small-scale producers in Mwanza region, using a stochastic frontier production function approach. A randomly selected sample of participants in the two districts was used. The Maximum Likelihood estimation procedure was followed to obtain the determinants of technical efficiency and technical efficiency levels of small-scale maize producers. The minimum and maximum values of technical efficiency were between 20% and 91%, indicating that the least practices of specific producer operates at a minimum level of 20%, while the best practice producers operate at 91% technical efficiency level respectively. The summary results of the mean technical efficiency was 63%. The main determinants of technical efficiency were labour, farm size, producer's experience, producer's age, family size which were all positive and statistically significant. The findings suggest that the average efficiency of small-scale maize producers could be improved by 37% through better use of existing resources and technology. These findings highlight the need for action by government to assist small-scale maize producers improve efficiency.

**Keywords**--- Maize, technical efficiency, small-scale producers, Mwanza Region, Tanzania

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## 1. INTRODUCTION

Maize is the major staple food in Tanzania. It is also the dominant food crop produced by the majority of small-scale producers. Maize is produced by four different groups in the country. The first group and the most important, is composed of smallholders with less than 10 hectares with 2 or 3 ha, but contributing about 80% of total production. The second group consists of village farms (Ujamaa) with 10-100 ha, and contributing about 5-10%. The third group consists of large farms with holdings bigger than 100 ha and contributing about 5%. The fourth group consists of private and public very large farms, contributing another 5%. In the Southern Highlands the small farmers are relatively more important than the other groups. In 2020, the country's maize production was 6,300 thousand tonnes. Maize production increased from 715 thousand tonnes in 1971 to 6,300 thousand tonnes in 2020 growing at an average annual rate of 6.41% (Knoema.com, 2020). However, maize production by small-scale producers, although being the main maize producers in the country, has remained in low productivity (Ngogwe and Kongolo, 2020). In order to market demand for maize, small farmers should be encouraged to produce more maize under the conditions of increasing productivity. One of the key factors for improving maize productive efficiency is to increase the technical efficiency of small-scale maize producers (Mango et al, 2015). The concept of productive efficiency includes two components, technical allocative and economic efficiencies (Boundeth et al., 2012). Technical efficiency (TE) is the producer's ability to produce maximum possible output with a minimum quantity of inputs, under a given technology (Hayatullah, 2017). Allocative efficiency (AE) reflects the ability of a firm to use the inputs in optimal proportions in order to produce. Economic efficiency (EE), combines technical and allocative efficiency by measuring the producer's overall performance (Amos, 2007). Limited capacity of farmers are often attributed to low productivity. That is, farmer needs more inputs such as technology, farm size and fertile soil. Elibariki et al. (2008) noted that increasing the productivity cannot only be achieved through inputs and technological innovation, but also through more efficient use of resources and skill at farmer's level. Increasing productive efficiency by improving technical efficiency would be more cost effective than introducing new technology as a means of increasing output (Boundeth et al., 2012). The findings of this study will be useful to both maize producers and planners to revisit maize production and productivity. Given the above background, the purpose of this study was to estimate technical efficiency and its determinants in maize production by small-scale producers in Mwanza Region.

### 1.1 The Problem Statement

Maize has the great potential to lead as the cereal constituent of intercrop and it is often combined with dissimilar crops (Memon et al., 2016; Abdulai et al., 2018). It is equally well accepted for feed ingredient and can contribute up to 30% protein, 60% energy, and 90% starch in animal diet (Shehu et al., 2007). Maize production in Tanzania is predominated by small-scale

producers who use traditional methods of production. Because of low yields, up to 80% of all maize is consumed by the producing households (FAO, 2015; Hayatullah, 2017). Changes are needed to help millions of small-scale farmers who currently make little or no profit from maize production to become profitable (Mango et al, 2015). Generally, small-scale maize production yields are low. To achieve optimum production level, resources available must be used efficiently (World Bank, 2015). Scarce resources are underutilized in addition to the use of low yielding varieties, poor extension services, inadequate incentives and amenities giving rise to low output leading to low farm income (Abdulai et al., 2018).

Small scale farmer is typically characterized by the size of land ownership being less than 2-10 hectares. They operate mostly in rural areas, and are the biggest group in the agriculture sector as a whole (Misaki et al., 2016). Generally, small-scale producers cultivate an average area of 1.23 hectares of crops scattered around the farming community. With this average plot size, the majority cannot afford the use of manure, fertilizer and improved seeds (Boundeth et al, 2012). Small scale agricultural sector has remained poor for various reasons, namely: unproductive agriculture practices, low productivity of land, low input qualities, underdeveloped irrigation system, limited access to capital, limited technology, poor infrastructure, lack of extension services, lack of pests and diseases know-how, lack of information, soil degradation, poor network system, and inability to access and use agricultural related information (Misaki et al., 2016).

Measuring economic performance of a small - scale maize producers requires an understanding of their production decisions and their levels of technical efficiency. Technical efficiency as a precondition for economic efficiency safeguards the economic viability and sustainability of a producer (Hayatullah, 2017). Maize productivity can be improved by adopting and introducing new technology such as new machinery, chemicals, and improved seed varieties. Alternatively, productivity can be enhanced by changing how factors are combined to improve the efficiency through which inputs are being transformed into output, such that higher outputs are produced from the same level of inputs and technology. Production decisions by farmers also affect the level of technical efficiency and the overall productivity of a farmer (Mango et al, 2015). The study aims at examining and estimating both technical efficiency and its determinants by answering the following questions:

1. What is the range of technical efficiency of small-scale maize producers in the region?
2. What are the determinants of technical efficiency of maize producers in the area?

## **2. REVIEW OF RELATED LITERATURE**

### **2.1 Stochastic frontier analysis (SFA) concept**

Briefly speaking, a stochastic frontier analysis (SFA) is a method of economic modeling. It has its starting point in the stochastic production frontier models introduced by Aigner et al, (1977). Recently, various non-parametric and semi-parametric approaches were proposed and introduced in the literature, where no parametric assumption on the functional form of the production relationship was made (Hayatullah, 2017). A stochastic frontier production model which was proposed by Battese and Coelli (1995) adds to the original models by Aigner et al., (1977); and Meeusen and van den Broeck (1977) used to estimate productive technical efficiency of the farmers. In agriculture, the stochastic frontier approach is considered to capture measurement error and other statistical noise influencing the shape and position of the production frontier (Hayatullah, 2017).

### **2.2 Technical efficiency**

Technical efficiency is a way through which individual farmer can transform inputs into outputs given set of technology and economic factors. Two farmers using the same kind of inputs and technology may produce considerably different levels of output (Abdul-Rahaman, 2016). Technical efficiency concept relates to individual farmer's production performance which can be compared to the best practice input-output relationship. The best-practice frontier is assumed to be stochastic, with a corresponding two-sided error term, in order to capture exogenous shocks beyond the control of the farmers. Since all farms are not able to produce the frontier output, an additional one-sided error term is introduced to represent technical inefficiency (Battese and Coelli, 1995).

Mango et al (2015) argue that technical efficiency is the ability of a farming unit to produce a maximum level of output given the level of input. Hayatullah (2017) posits that the two important approaches to technical efficiency extensively used in the efficiency literature include: (1) Parametric Stochastic Frontier Analysis (SFA), initially proposed by Aigner et al., (1977) and (2) Nonparametric Data Envelopment Analysis (DEA), initially proposed by Cooper et al. (2011). Hayatullah (2017), said that technical efficiency estimates obtained from nonparametric approach (DEA) are generally lower than those obtained under the parametric (SFA) alternative (Coelli et al, 2005; Hayatullah (2017). The main advantage of the econometric / parametric stochastic frontier analysis (SFA) approach is that it incorporates a composed error structure with a two-sided symmetric term and a one-sided component which allows to distinguish between inefficiency and exogenous shocks (Aigner et al., 1977; Mango et al, 2015; Hayatullah (2017). The degree of technical inefficiency reflects an individual farmer's failure to attain the highest possible output level given the set of inputs and technology represented by the production frontier (Mango et al, 2015).

### 2.3 Technical efficiency empirical studies

Among the various empirical studies that have examined technical efficiency, some few such studies were examined in this work. Boundeth et al, (2012) used Cobb-Douglas and translog stochastic frontier production functions to estimate technical efficiency (TE) and its determinants in maize yield in Laos. Their findings indicated that labour and machinery costs were positive and significant on maize yield. The mean technical efficiency was 65%, suggesting that the output per farm could be increased by 35% on an average for maize producers working under prevailing technology, with no change in inputs. About 31% of producers in sample had a technical efficiency score of more than 81%. For educated and experienced producers, farm size, and hybrid seed variables have the potential to reduce technical inefficiency.

Abdul-Rahaman (2016) used a Stochastic frontier analysis (SFA) of technical efficiency to investigate smallholder cotton farmers in Ghana. A multi-stage sampling procedure was employed to select 150 smallholder cotton farmers in the 2009 growing season. Maximum likelihood estimation procedure was used to obtain the determinants of technical efficiency and technical efficiency levels of cotton farmers. The results showed that smallholder cotton farmers' technical efficiency in the area was between 16.05% and 98.13%, with mean efficiency score of 84.5%, suggesting that average smallholder cotton farmer in the Region would have produced 15.05% more output with the same level of inputs, if the farmers were to produce on the most technically efficient frontier. The main determinants of technical efficiency included age, association membership, education, family size, age of farm, extension visits and cotton farmer's experience.

Mango et al., (2015), conducted a stochastic frontier analysis of technical efficiency in smallholder maize production in Zimbabwe's smallholder farming communities. A stochastic frontier production model was applied, using a linearised Cobb–Douglas production function to determine the production elasticity coefficients of inputs, technical efficiency and the determinants of efficiency. The findings suggested that maize output responded positively to increases in inorganic fertilisers, seed quantity, labour used and area planted. The technical efficiency analysis suggested that about 90% of farmers in the sample were between 60% and 75% efficient, with an average sample efficiency of 65%. The significant determinants of technical efficiency were gender of the household head, household size, frequency of extension services, farm size and the farming region.

## 3. METHODOLOGY

The study methodology was carefully designed to maximize the use of available quantitative information (Corbin and Strauss, 2008). Therefore, quantitative research designs was used to achieve the objectives of the study. This study adopted stochastic frontier approach following agricultural production's tendency to exhibit random shocks. Hence, there was a need to separate the influence of stochastic factors (random shocks and measurement errors) from the effects of other inefficiency factors by assuming that deviation from the production frontier may not be entirely under the control of farmers (Hayatullah, 2017).

### 3.1 Research area

The study was conducted in Mwanza, one of Tanzania's 31 administrative regions. The region has 8 districts namely: Nyamagane, Ilemela, Magu, Kwimba, Misungwi, Geita, Sengerema, and Ukerewe, with a total population of about 3,125,995 and, it is the second largest region after Daressalaam (Ngogwe and Kongolo, 2020) (Figure 1).



Figure 1. Mwanza regional map

The regional capital Mwanza lies in the northern part of the country, located between latitude 1° 30' and 3° south of the Equator. Longitudinally the region is located between 31° 45' and 34° 10' east of Greenwich. The region shares borders with Lake Victoria in the North, Kagera and Geita in the West, Mara Region in the East, while Shinyanga and Simiyu

regions are located on the South and South-eastern side of the region (URT, 2017). Mwanza is a relatively small region occupying 2.3% of the total land area of Tanzania mainland. The region occupies a total of 35,187 sq km., out of this area 20,095 sq km is dry land and 15,092 sq km is covered by Lake Victoria. The Region’s 43% of surface area is covered by water, the remaining 57% of surface is a dry land as shown in Figure 2 (URT, 1999).

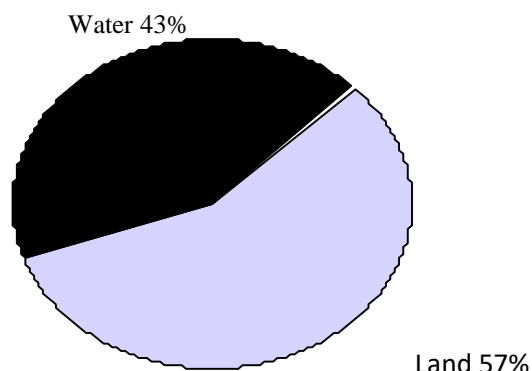


Figure 2: Distribution of surface area, Mwanza region

### 3.2 Sample and data collection

The sampling frame was drawn from small-scale farmer households in two selected districts. They included Nyamagana and Ilemela districts which were purposively selected because of their maize production potential. From the sampled two districts, three (3) wards were randomly selected per district and 13 small-scale maize producers randomly chosen from each of the three selected wards. It resulted in a total of seventy-eight (78) participants randomly sampled during the study period. The three wards included Usagara, Misungwi and Kisesa. Through review of literature, quantitative secondary data was gathered from various sources, namely: (1) Tanzania annual agricultural sample survey report (2014/2015); (2) Tanzania CGAP smallholder surveys report (2016); (3) Tanzania annual agricultural sample survey (2016/2017); and (4) Tanzania National Bureau of Statistics (2016/2017) annual survey. This allowed the author to make effective use of information already available while conceptualizing the assessment, thus being able to focus on quantitative data to fill the key information gaps (Astalin, 2013). Important socio-economic variables gathered included age, sex, level of education, farm size and farming experience. Socio-economic characteristics were widely believed in the literature to influence efficiency (Hayatullah, 2017).

### 3.3 The model

This study adopts the stochastic frontier function because following the reason given previously in (3). Stochastic frontier production function is estimated following Aigner et al. (1977); (Boundeth et al., 2012); Mango et al (2015). One advantage of this approach is that it accounts for measurement error in the specification and estimation of the frontier production function (Mango et al, 2015). The stochastic frontier production model used follows Adzawla et al. (2013), Abdul-Rahaman (2016) and Hayatullah, 2017) and it is specified as:

$$Y_i = f(X_i; \beta) - U_i + V_i, \text{ given that } i = 1, 2, \dots, n \quad (1)$$

where  $Y_i$  is output of  $i^{th}$  maize producer;  $X_i$  is a (1 Xk) vector of farm inputs used in maize production;  $\beta$  is a (kX 1) vector of parameters to be estimated.  $V_i$  is a random error variation in maize output) associated with random factors not under the control of the farmer while  $U_i$  is inefficiency effects. The assumptions that the model includes random error  $V_i$  is assumed to be independently and identically distributed with mean zero and constant variance -  $N(0, \sigma_v^2)$  and independent of  $U_i$ , and that the non-negative error  $U_i$  is distributed as the absolute value of a normal distribution,  $N(0, \sigma_u^2)$  (Mango et al, 2015; Hayatullah, 2017). The technical efficiency of an individual producer can be defined in terms of the ratio of the observed output to the corresponding frontier output, given the available technology (Boundeth, 2012).

### 3.4 Tests model specification

There exist various ways to tests the null hypotheses of the frontier production functions. The Maximum likelihood estimates (MLE) for all parameters of the stochastic frontier production and inefficiency were also estimated including the variance parameters in terms of parameterization (Boundeth et al., 2012). The variance parameters were specified as:

$$\sigma^2 = \sigma^2_v + \sigma^2_u \quad (2)$$

and

$$\gamma = \sigma^2_u / \sigma^2 \quad (3)$$

to have  $0 \leq \gamma \leq 1$

From equation (3) it can be noticed that  $\gamma$  ranges from 0 to 1 taking the values close to 1, indicating that the random component of the inefficiency effects contributes positively to the analysis of the production system (Hayatullah, 2017). Thus, the technical efficiency (TE<sub>i</sub>) of the i-th producer was expressed in terms of the levels of inputs used, and it can be estimated using the expectation of  $U_i$  conditional on the random variable  $\varepsilon_i$  (Maongo et al, 2015; Abdul-Rahaman (2016) as expressed in the following equation:

$$TE_i = \text{Exp}(-U_i) \quad TE_i = \text{Exp}(-U_i) \quad (4)$$

The Technical Efficiency (TE) of a small-scale producer was between 0 and 1 and is inversely related to the level of the technical inefficiency effects (Boundeth et al., 2012). The TE is also predicted using the Frontier 4.1 package, used to calculate the ML estimate of the predictor for equation (6), that is based on its conditional expectation, given the observed value of  $(V_i - U_i)$ . If  $U_i$  is equal to 0, the production is on the frontier and the producer is technical efficiency. If  $U_i$  is greater than 0, the production will lie below the frontier and the producer is technical inefficiency (Mango et al, 2015). The technical inefficiency can only be estimated if the inefficiency effects are stochastic and have a particular distribution specification (Boundeth et al., 2012). It follows that the technical inefficiency determinants of small-scale maize producers were expressed as follows:

$$\ln(U_i) = \delta_0 + \delta_1(C_i) + W_i \quad \ln(U_i) = \delta_0 + \delta_1(C_i) + W_i \quad (5)$$

where  $U_i$  is technical inefficiency;  $\delta_0, \dots, \delta_1$  are the parameters to be estimated;  $C_i$  is a vector of farmer and household socio-economic characteristics;  $W_i$  is a random error.

### 3.5 Empirical model

The study used of stochastic frontier approach to estimate the level of technical efficiency of small-scale maize producers including the levels of the determinants of inefficiency of producers.

The empirical model used was expressed in the following form of Cobb-Douglas frontier production function (Binam et al., 2004; Mango et al, 2015).

$$\ln Y_i = \beta_0 + \beta_1 \ln X_1 + \beta_2 \ln X_2 + \beta_3 \ln X_3 + \beta_4 \ln X_4 + \beta_5 \ln X_5 + \beta_6 \ln X_6 + \beta_7 \ln X_7 + \beta_8 \ln X_8 + \beta_9 \ln X_9 + \dots + V_i - U_i \quad (6)$$

where  $Y_i$  is output (kg);  $X_1$  is labour (man-hours);  $X_2$  is seed (kg/ha);  $X_3$  is fertilizer (kg);  $X_4$  is farm size (ha);  $X_5$  is farming experience;  $X_6$  is age of farm (year);  $X_7$  is family size;  $X_8$  is education level;  $X_9$  is extension visits (number);  $\beta_s$  are parameters to be estimated, and  $V_t$  is the random variation in output.

## 4. RESULTS AND DISCUSSION

The demographic data show that about 65.6% were males and 44.4% were female households. The majority of small-scale producers (73.7%) had completed primary school, the remaining 26.3% had completed secondary school. The total farming area was about 23 61ac3 on average (min of 2ac and max of 120ac). The total area of land cultivated was 12.08ac on average (min of 2.5ac and max of 84ac). The total monthly income was about TZS87,762 on average, ranging between TZS34.000 to ZS250.000. The number of people in household was about 5.86 on average, ranging from 2 to 10 people. The major crops cultivated by small-scale producers included maize, sunflower, and legumes to some extent. The results in table 1 indicate that the average yield per hectare in maize production by small-scale producers is about 1.48 kg, which is relatively good given the conditions in which they operate (Table 1).



Table 1: Summary statistics of selected variables of the model

Variable	Mean	Standard Deviation	Minimum	Maximum
<b><i>Production function model variables</i></b>				
Yi - Output/Yield (kg/ha)	1.48	0.68	1.20	2.04
X1 – Labour (man/hours)	1.28	1,78	0.56	2.18
X2 – Seeds (kg/ha)	0.16	0.13	1.19	2.09
X3 – Fertilizer/manure (kg/ha)	0.40	0.02	0.26	0.78
X4- Farm size (ha)	1.23	0.78	0.24	3.00
<b><i>Inefficiency model variables</i></b>				
X4 – Age of farmer (year)	36.19	5.20	23.00	65.00
X5 – Education (years)	0.84	0.17	0.01	2.00
X6 - Farming experience (year)	8.29	3.36	1.07	15.00
X7 - Family size (number)	5.27	2.79	2.00	6.38
X8 – Association membership	2.18	5.33	0.00	4.21
X9 – Extension visits (Number)	2.48	6.21	0.00	5.14

Source: Research data (2021).

**Notes:** US\$ 1 = TZS 2,339. Education dummy value is 1 if farmer completed primary school, and 0 otherwise.

However, the interval between minimum and maximum of maize yield suggests 1.20 and 2.04 Kg respectively. The results also reveal that about 89% of maize producers do not use fertilizer and most of them grow maize on the upland area. The labour cost mean was about TZS1.28 million per hectare, equivalent to about 62 man- days per hectare. This finding is in line with the finding of Ngogwe and Kongolo (2020) who analysed resources use efficiency in small-scale maize production in Mwanza Region. Their findings indicated that about 93% of small-scale maize farmers use hired labour, seeds and fertilizer. Farm size of about 1.23ha is the normal size for an average small-scale producer in developing area (Misaki et al., 2016). The average age of the farmers was 36 year and above. In terms of educational levels, about 85% of maize farmers had primary school education. Small-scale producers experience ranged from 1 year to 15 years maximum and 8 years on average. Family size was about 2 persons to 8 maximum and 5 people on average. In terms of membership association it was argued that 2 out of 10 small-scale producers were interested in becoming members of association. Lastly, extension variable suggests that visits by extensionists to the study area were not enough in assisting small-scale producers increase maize production.

#### 4.1 Technical efficiency

The technical efficiency was measured by the maximum-likelihood estimates model (MLE) using parameters of the Cobb-Douglas function defined by Equations 4, 5 and 6 presented in Table 2. The findings suggest that the coefficient of labour was positive and statistically significant at 1% level ( $P < 0.01$ ) for both Cobb-Douglas and translog functions. That is, 1% increase in labour costs will result in an increase in maize yield of about 0.62% with Cobb-Douglas function and 31% with translog function respectively. This may be a reality given that the majority of small-scale maize producers in the study area relies heavily on labour, particularly when it comes to clearing field, planting, weeding and harvesting (Bravo-Ureta, 2007; Boundeth et al, 2012; Mango et al, 2015). Both the coefficients of seeds and fertilizers were negative and statistically insignificant. They suggested that most small-scale maize producers do not have access to fertilizer and improved seeds for their maize crop, as a result their maize yield cannot be improved to some extent. The negative signs of both seeds and fertilizer coefficients may mean that both seeds and fertilizer do not have any positive impact on maize yield. The above two findings were in contradiction with the findings of Boundeth et al, (2012) and Mango et al, (2015) on their studies on technical efficient in smallholders maize production in Laos and Zimbabwe respectively. The coefficient of farm size was positive and statistically significant at the 10% level for both Cobb-Douglas and Translog functions. It implied that with 10% increase in farm size will result in an increase in maize yield of about 29% with Cobb-Douglas function and 20% with translog function respectively. The parameter estimates of both farmer experience and age of the farmer were all positive and statistically significant at the 1% ( $P < 0.001$ ) in Cobb-Douglas functions. Farmer with more farming experience can produce more output at the same time increase technical efficiency (Memon et al, 2006). Overall, as maize farmer's experience increases in the number of years of farming, the technical efficiency also increases leading to the best practices in the running of agricultural activities to reduce inefficiency. On the other hand, the parameter of age of small-scale maize producer positively affects maize production. In different terms, as small-scale maize producer advances in age, maize productivity also increases by becoming more experienced. This enables the effective execution of maize farming operations (Abdul-Rahaman, 2016). The results of Maximum Likelihood Estimates (MLE) are in Table 2.

Table 2: Maximum Likelihood Estimates (MLE) of the stochastic production frontier model of the determinants of maize output.

Variable	Parameters	Cobb-Douglas Production Model		Translog Production Model	
		Coefficients	t-values	Coefficients	t-values
		Constant	Bo	3.905	1.164
Labour	$\beta_1$	0.158	0.624***	0.272	0.313**
Seed	$\beta_2$	-0.090	-0.023	-0.008	-0.005
Fertilizer	$\beta_3$	-0.027	0.013	-0.018	0.037
Farm size	$\beta_4$	0.068	0.293*	0.231	0.199*
Experience	$\beta_5$	0.497	4.387***	0.279	0.642***
Age of farmer	$\beta_6$	0.074	0.613***	0.714	0.428***
Family size	$\beta_7$	0.438	1.330***	0.926	1.371***
Education	$\beta_8$	-0.202	-1.537*	-0.418	-1.114*
Extension visits	$\beta_9$	-0.127	0.347*	-0.512	-1.353*
Sigma squared $\sigma^2_s = \sigma^2_v + \sigma^2_u$	$\sigma^2$	0.892	3.338***	0.212	0.86*
Gamma $\gamma = \sigma^2_u / \sigma^2$	$\gamma$	0.537	3.462***	0.884	21.66***
Log likelihood function		-11.231		20.046	
LR test of one sided error		28.39		57.37	
N = 78					

Source: Research data, (2021).

The finding on age in this study supports the finding of Abedullah and Ahmad, (2006); however, it contradicts the finding of Shehu et al. (2007) which reported that the age of farmer impacts positively on the inefficiency in production. The parameter estimate of family size as one of the determinants of technical efficiency was positive and statistically significant at the 1% ( $P < 0.01$ ). It indicated that the larger the family, the more labour a farmer has in increasing the output, hence technical efficiency (Boundeth et al., (2012). The coefficient of education was negative but significant at the 10% level. It suggested low level of understanding of agricultural related production information. Generally, producers with access to education are able understand agricultural extension advice on how to increase the output. This is consistent with the findings of Abdul-Rahaman (2015) and Mango et al, (2017). The parameter estimate of extension visits was negative and statistically insignificant. It implies that most small-scale maize producers were not visited by extension officers to be advised on agricultural issues on a regular basis to be more technically efficient in maize production. This finding contradict the finding by Abdul-Rahaman, (2016) who found that extension visits increased technical efficiency of smallholder cotton farmers in Ghana.

Concerning the determinants of technical efficiency, from the analysis of both Cobb-Douglas and Translog production function, the determinants of technical efficiency of the small-scale maize producers in the study area were labour, farm size, farming experience, age of farmer, and family size. These variables play critical role in increasing the technical efficiency of the small-scale maize producers significantly. In terms of the sources of inefficiency of the small-scale maize producers in the study area, firstly, one-side error term of the technical inefficiency function model  $\mu_i$  was considered as expressed in equation (6), then reported in table 2. After analysis, the results of technical inefficiency model indicated that the parameter estimates for sources of inefficiency variables were almost the same from the analysis of both Cobb-Douglas and translog production functions. From the results in table 2, it can be observed that the coefficients of the parameters seeds, fertilizer, education and extension were all statistically insignificant in Cobb-Douglas and translog production functions. The negative signs of the parameters correlate positively with technical inefficiency rather than technical efficiency of the small-scale producers (Abedullah and Ahmad, 2006; Abdul-Rahaman, 2016).

#### 4.2 Hypothesis testing

As expressed in 3.4, equation 3 defines the parameter  $\gamma$  as ( $\gamma = \sigma^2_u / \sigma^2$ ) taking the values 0 to 1. That is, if  $\gamma = 0$ , it indicates the absence of technical efficiency, but if  $\gamma$  takes a value less or equals to 1, it indicates that the frontier model is relevant and appropriate or  $\gamma = 1$ . From Table 2, we see that the value of  $\gamma$  associated with the variance in the stochastic frontier was 0.537 and it is statistically significant at the 1% ( $P < 0.001$ ). This value indicates that about 0.537% of the difference between observed output and maximum production frontier results from the difference in producer's level of technical efficiency rather than random variability. The LR (Likelihood Ratio) test of the one side error of  $\gamma$  was expressed following

the Chi-square ( $\chi^2$ ) distribution and was used to test the null hypothesis of Cobb-Douglas and translog  $H_0 = \delta_0 = \dots \delta_n = 0 = \gamma$ . The test statistic was performed to estimate the value of “LR” of Cobb-Douglas and translog equations of 28.39 and 57.37 respectively. The values were greater than the values in the ( $\chi^2$ ) distribution at 1% level with 1 degree of freedom. Therefore, the null hypothesis of no technical inefficiency effect among small-scale maize producers was disregarded and rejected. The null hypothesis rejection was in a form of supporting the presence of inefficiency that exists among small-scale maize producers in the study area, based on the empirical results of both Cobb-Douglas and translog production functions.

#### **4.3 Technical efficiency scores**

This study estimated the stochastic frontier production function to determine technical efficiency of small-scale maize producers in Mwanza region. The frequency distribution of the producer specific technical efficiency is summarised in this section. The minimum and maximum values of technical efficiency were between 20% and 91%, indicating that the least practices of specific producer operates at a minimum level of 20%, while the best practice producers operates at 91% technical efficiency level respectively. Overall, the summary results of the mean technical efficiency was 63%. Suggesting that more opportunities exist for small-scale maize producers to improve technical efficiency by about 37% on average, based on the current set of technology and inputs to their disposal. In addition, the average small-scale maize producer could reduce the costs of production by 37% if all of them achieved the highest level of technical efficiency of 91% (Boundeth et al, 2012). The 63% mean technical efficiency in this study was compared with other mean technical efficiencies obtained in previous studies of 84.4%; 65% and 65% respectively (Abedullah and Ahmad, 2006; Boundeth et al, 2012; Mango et al, 2017). It can be argued that this study’s mean technical efficiency compares well with those of the previous studies, but was lower to that of Abedullah and Ahmad, (2006); mean technical efficiency of 84.4%. These results suggest that small-scale maize producers in the study area are constrained by a number of factors which include scarcity of extension visits, small size of areas planted, low level of education, and low agricultural potential areas. The potential for increasing the average efficiency among small-scale maize producers in Mwanza seems to be significant, about 37% (Mango et al, 2015).

#### **4.4 Conclusion**

The aim of this study was to analyse technical efficiency and its determinants of small-scale maize producers in Mwanza region, Tanzania. Data used was collected from various sources with identified factors related to technical efficiency from a sample of 78 small-scale maize producers. The technical efficiency and its determinants were examined through the Cobb-Douglas and translog production functions. The findings indicated that labour, farm size, producer experience, age of the producers, and family size variables responded positively to maize production by being statistically significant on maize yields. However, seeds, fertilizer, education levels, and extension visits variables have had negative signs and were not significant. That is, they were not sources of technical efficiency of the small-scale maize producers but potential sources of inefficiency (Boundeth et al, 2012). Variations in minimum and maximum technical efficiency were 20% and 91% respectively. The mean technical efficiency of the total sample of producers was 63% of maximum attainable output for a given set of input levels and the technology. This implies that the output per producer can be increased on average by 37% of maize producers under the current conditions. The findings of this study are in line with the findings of Abedullah and Ahmad, (2006); Boundeth et al, (2012); Mango et al, (2015) technical efficiency analysis of smallholder potato production in Pakistan, maize production in Zimbabwe and Laos respectively. The Maximum Likelihood Estimate (MLE) evidences the need for efficient use of available means of production. The MLE estimates were based on the coefficient of gamma ( $\gamma$ ), the ratio of the variance of technical inefficiency effects ( $U_i$ ) to the variance of random errors ( $V_i$ ). All parameters of the technical efficiency were analysed using Cobb-Douglas and Translog production functions. This coefficient was estimated to the value of 0.884 on translog function and which was statistically significant at 1% level. It implied that about 88.4% of the variation in maize output was attributable to differences in technical efficiencies among small-scale maize producers. The challenge was that about 11.6% of the variation in the maize output among the small-scale maize producers belong to random shocks, namely: unfavourable weather conditions, breakage of farming tools and other factors not under the control of the cotton farmers.

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