# AN ASSESSMENT OF EFFECT OF INPUT SUBSIDIES ON ECONOMIC EFFICIENCY OF SORGHUM PRODUCERS IN BOTSWANA

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## DECLARATION

This research thesis is my original work and has not been submitted at any University for a degree.

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# DEDICATION

I dedicate this work to my parents for their support in my academic journey.

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| | |
|---|---|
| ALDEP: | Arable Lands Development Programme |
| ARAP: | Accelerated Rainfed Arable Programme |
| ASTI | Agricultural Science, Technology and Innovation |
| BAMB: | Botswana Agricultural Marketing Board |
| BIDPA: | Botswana Institute for Development Policy |
| CEDA: | Citizen Entrepreurial Development Agency |
| DEA: | Data Envelopment Analysis |
| ISPAAD: | Integrated Support Programme for Arable Agriculture |
| LR: | Likelihood ratio |
| MT: | Metric tonnes |
| NAMPAAD: | National Master Plan for Arable Agriculture and Dairy Development |
| SADC | Southern African Development Community |
| SFA: | Stochastic Frontier Analysis |
| TFA: | Thick Frontier Approach |
| UNDP: | United Nation Development Program |
| US$: | United States of American dollar |

## ABSTRACT

Sorghum remains an important component in Batswana's diet and has the ability to adapt to semi-arid areas of Botswana. In order to increase its productivity, the Government of Botswana has put in place an input subsidy programme. However, the productivity of sorghum remains low compared to that of Botswana's neighbors. The purpose of the study, therefore, was to evaluate the effect of input subsidies on the economic efficiency of sorghum producers in Botswana as a means to evaluate whether input subsidy has positive or negative effect on the economic efficiency of sorghum producers. Secondary data were used covering the period between 1998 and 2017. The data were collected from both domestic (Botswana's Ministry of Agriculture, Statistics Botswana, Bank of Botswana and Botswana's Department of Meteorological Services) and international (the Food and Agriculture Organization of the United Nations, International Labour Organization, the Agricultural Science, Technology and Innovation, and World Bank) databases. A stochastic production frontier was used to compute technical efficiency while a stochastic cost function estimated the allocative efficiency. The two efficiencies were then multiplied to obtain economic efficiency. The effect of input subsidies on economic efficiency was assessed using a Tobit model. The results revealed that input subsidies had a positive and significant effect on economic efficiency; however, rainfall variability and trade openness affected it negatively. Sorghum farmers were both technically and allocatively inefficiency with average scores of 0.94 and 0.67 respectively. The study recommends that the Government of Botswana should increase input subsidies to sorghum as a climate risk-mitigating strategy particularly given the country's low and unreliable rainfall due to its semi-desert conditions. In addition, there is need to offer adult training programs to increase farmers' technical and allocative efficiency.


**Key words:** sorghum, input subsidy and economic efficiency

# CHAPTER ONE: INTRODUCTION

## 1.1 Background

Owing to institutional and economic factors, harsh physical environmental and climatic conditions in Botswana, agricultural productivity has declined over the last two decades, resulting an increase in the import of food staples such as sorghum and maize. Accordingly, Botswana imports 300,000 tonnes of cereals annually, which is over 90 percent of its local demand (UNDP, 2013). In order to ensure food self-sufficiency, the Government of Botswana (GoB) has over the years instituted various agricultural subsidy programmes. For instance, in 1980 the Accelerated Rain-fed Arable program (ARAP) and Arable Land Development Program (ALDEP) were formulated to provide implements and financial assistance to crop producers (Seleka et al., 2004). However, the ARAP proved unsustainable as farmers abandoned the use of implements (Seleka, 1999). During the ALDEP period, no significant change in the country's food self-sufficiency was realized as both output and crop yield did not experience any visible growth, hence the programme did not realize its aim of technology transfer (Centre for Applied Research, 2002).

Despite its poor performance, Botswana's agriculture sector still remains an important source of livelihood and employment for rural households. For example, more than 80 percent of people livelihood in Botswana depend on agriculture, and the sector employs about 30 percent of labour force (FAO, 2016). Arable farming in Botswana consists mainly of production of maize, millet, sorghum and pulses (Statistics Botswana, 2012). Sorghum is the main cereal consumed in Botswana, where the calorie supplies for 2013 stood at 173 kcal/capital/day (FAO, 2013).

Sorghum (*Sorghum bicolor*) is the main food staple in Botswana and thrives well under harsh climatic conditions. In particular, the sweet sorghum variety is well adapted to semi–arid conditions of Botswana with 300mm annual rainfall (Munyati et al., 2013). Almost every farming household in Botswana grows the sweet sorghum variety (Balole, 2003). In general, sorghum accounts for about 80 percent of proportion of the cultivated landscape, which is 23,359 hectares, (Statistics Botswana, 2013). In 2015, sorghum recorded the highest production of 38,992 metric tonnes (MT) followed by beans at 14,043 MT (Statistics Botswana, 2016). It also accounts for 19 percent of the local produce delivered to Botswana Agricultural marketing board (BAMB) after pulses (BAMB, 2015). About 72 percent of sorghum farmers are commercial based mainly in Borolong and Chobe districts (Statistics Botswana, 2016).

To further increase crop production to enhance national food security, the GoB implemented the Integrated Support Programme for Arable Agriculture Development (ISPAAD) in 2008 (FAO, 2018). The purpose of the programme was to offer free seed, fertilizer, improve access to portable water and draught power to farmers (Marumo et al., 2014). Following the implementation of the ISPAAD, the number of farmers involved in crop production increased from 31,000 to 118,000 farmers between 2008 and 2011(Marumo et al., 2014. In addition, the cultivated area increased from 104,000 to 377,000 hectares between 2007 and 2011 (Marumo et al., 2014).

As a result of GoB's subsidization of arable farming, sorghum yield rose from 130 to 410 kg/ha between 1997 and 2011 (Marumo et al., 2014). However, historical data between 1979 and 2015 suggest that sorghum has the potential to produce over 100,000 tonnes in total output annually, while the potential yield under ISPAAD programme ranged between one and 2.5 ton/ha for traditional and commercial farmers respectively (Statistics Botswana, 2015). Because of low sorghum productivity, Botswana relies on imports from South Africa to plug the deficit in local production (Statistics Botswana, 2016). This raises the question of whether input subsidies have had any effect sorghum productivity in Botswana.

It is imperative, therefore to explore the role of input subsidies on sorghum productivity in Botswana. Previous studies have shown that input subsidies induce an increase in crop productivity (Denning et al., 2009; Dorward et al., 2014). Furthermore, input subsidies also serve as the potential way of incentivising farmers to purchase inputs at affordable prices since farmers lack access to credit (Dorward et al., 2014). Thus, input subsidies could provide a means to improve agricultural productivity and reduce food insecurity in Botswana. Accordingly, this study sought to establish the effect of the input subsidies on sorghum farmers' economic efficiency in Botswana.

### 1.2 Statement of the research problem

Crop production in Botswana is seriously constrained by low and varying rainfall, and relatively poor soils (Statistics Botswana, 2016). In particular, sorghum production is increasingly exposed to high climate-related risk due to its heavy reliance on rainfall. As a result, sorghum production in Botswana continues to experience limits on its expansion because of inadequate market access and marketing facilities, recurring drought, limited skills, recurring drought, and inadequate use of improved technology **(**UNDP, 2012). Accordingly, local sorghum production in Botswana has never met the local demand; hence, the country remains a net importer of sorghum (UNDP, 2012).

In order to meet Botswana's food security objectives, the country has implemented various input subsidies to enhance crop (including sorghum) productivity among local farmers (Seleka et al., 2004). However, local sorghum production still remains low and has not met local demand (FAO, 2016). This begs the question about how the government-led input subsidy programs have affected both the technical and allocative efficiency of sorghum production in Botswana.

One of the input subsidy programs implemented by the GoB since 2008 is ISPAAD. The aim of the program was to improve crop productivity through increased access to inputs. The programme provided farmers with portable water sources, fertilizer, seeds, herbicides, improved access to financial assistance and fencing and establishment of agricultural centers Marumo et al., 2014). ISPAAD programme categorized farmers into three groups: subsistence, emerging and commercial. Farmers under the subsistence category cultivate a maximum of 16 hectares and are provided with free hybrid seeds for 5 hectares, open pollinated seeds for the remaining land size and free fertilizer and herbicides for 5 hectares (Ministry of Agriculture Botswana, 2013). Farmers in the emerging category cultivate a maximum of 150 hectares and are subsidized with 35 percent of their total costs of hybrid seeds and fertilizer (Ministry of Agriculture Botswana, 2013). Commercial farmers cultivate over 150 hectares and are assisted with 30 percent of total costs of hybrid seeds and fertilizer for 50 hectares (Ministry of Agriculture Botswana, 2013).

Various studies have evaluated the performance of ISPAAD and other agricultural subsidy programmes in Botswana. For example, Seleka (1999) evaluated the impact of ARAP on arable agriculture, and found that the programme was effective in improving household food security and welfare through increases cultivated area and yield.

Marumo et al. (2014) evaluated the social and poverty impacts of the ISPAAD and found that the input subsidy had no impact on poverty reduction as 70 percent of beneficiaries still lived below the World bank poverty line of 1.90 US$/day even with the ISPAAD.

A thorough review of literature yields virtually no study that has focused on the effect of input subsidies on economic efficiency of sorghum producers in Botswana. In particular, while the studies highlighted above have evaluated the effectiveness of ISPAAD on poverty and crop production, no study has so far been undertaken to assess the effect of the programme on both technical and allocative efficiency of sorghum farmers in the country. Elsewhere in Africa, studies show mixed evidence on the effect of input subsidies on economic efficiency. For example, while Darko (2013) found a positive relationship between input subsidy and technical efficiency of farmers in Malawi, Chiromo (2018) found no such relationship in the same country. In assessing the effect of input subsidies on economic efficiency of sorghum producers in Botswana, this study also sought to clarify – through further evidence – the relationship between input subsidies and economic efficiency using Botswana as a case study.

## 1.3 Purpose and Objectives of the Study

The purpose of this study was to examine the effect of input subsidies on economic efficiency of sorghum producers in Botswana. The specific objectives were:

1. To estimate the economic efficiency of sorghum producers in Botswana.
2. To assess the effect of agricultural input subsidies on the economic efficiency of sorghum producers in Botswana.

## 1.4 Study hypotheses

The following hypotheses were tested:

1. That sorghum producers in Botswana are technically inefficient.
2. That sorghum producers in Botswana are allocative inefficient.
3. That sorghum producers in Botswana are economic inefficient.
4. That input subsidies have no effect on the economic efficiency of sorghum producers in Botswana.

## 1.5 Justification of the study

Sorghum is the most essential food staple in Botswana and it is the main crop cultivated under commercial farming. This study examined the effect of input subsidies on economic efficiency of sorghum producers in Botswana to identify the sources of technical and allocative inefficiencies. The findings of the study will help policy makers formulate appropriate policies aimed at eliminating those inefficiencies, which is expected to enhance the economic efficiency of sorghum producers in Botswana. In addition, the findings will enable the GoB measure the effect of its ISPAAD subsidy program among sorghum producers in order to determine whether or not to continue supporting it. The findings will also be useful to sorghum farmers who will understand the sources of inefficiency in their production efforts.

This study fits in the GoB's national vision 2036 under the pillar of economic development. This is because an improvement in productivity in sorghum will aid Botswana's economy to reduce its reliance on food imports. The reduction of inefficiencies in production will aid producers to minimize costs. The study contributes to Sustainable Development Goals (SDG) 1 and 2 of no poverty and elimination of hunger respectively. The use of various analytical techniques to assess technical, allocative and economic efficiency contributes to the existing stock of scientific knowledge.

## 1.6 Limitation of the study

Due to data limitations, the study covered 20 years from 1998 to 2017. Additionally, it was difficult to obtain retail prices of inputs and products; hence, import prices were used instead. The import prices were adjusted for inflation using implicit price deflator.

## 1.7 Organization of thesis

The thesis is organized into five chapters. The first chapter covers the introduction of the study, which includes background information, statement of the problem, purpose and objectives, hypothesis, justification, limitation of the study and glossary of terms. Chapter Two presents the literature review, which covers both theoretical and empirical review. Chapter Three focuses on the methodology used in the study, presenting the theoretical and empirical frameworks, research design, data collection procedures and data analysis process. Chapter Four presents and discusses the findings of the study while Chapter Five gives the summary, conclusions and policy recommendations.

### 1.8 Glossary of terms

Allocative efficiency: optimal choice of factors of production given their prices.

Autocorrelation: process where the disturbance terms are no longer random.

Economic efficiency: entails getting more from the resources utilized.

Heteroscedasticity: process where the variance of disturbances terms varies.

Multicollinearity: existence of a linear relationship between some or all explanatory variables.

Stationarity: process where the mean and variance are constant over time, and the value of covariance depends on the distance of two time periods.

Technical efficiency: involves the ability of the firm to produce at a maximum output given the level of inputs used.

# CHAPTER TWO: LITERATURE REVIEW

## 2.1 Concept of economic efficiency

Efficiency is the ability of a firm to get more output from scarce resources leading to a reduction in production costs (Kumbhakar, 1993).). According to Charnes et al. (1978), efficiency is the degree to which the use of inputs to produce a given level of output matches with the optimal use of scarce resources. Its measurement relies on the specification of the production function, which represents the maximum outputs produced from the use of a given level of inputs (Chioma, 2017). Farrell (1957) defined efficiency as the capability of the firm to produce the maximum level of output with the use of available resources. According to Fried et al. (2008), efficiency is measured by comparing the observed output against the potential output.

The economics literature identifies three components of efficiency: (i) technical efficiency (TE), (ii) allocative efficiency (AE), and (iii) economic efficiency (EE). According to Farrell (1957), economic efficiency is the product of technical and allocative efficiency.

### 2.1.1 Technical efficiency

Technical efficiency (also called “production efficiency”) is the ability of the firm to produce the highest level of output using a given bundle of inputs (2005). This could involve either producing the same quantity of output using less resources or producing a higher level of output using the same level of inputs (Koopmans, 1951; Farrell, 1957).

### 2.1.2 Allocative efficiency

Allocative efficiency refers to the optimal choice of inputs given their respective prices (Tchale, 2005). A firm is considered to be allocatively efficient if it can choose the combination of resources to produce a certain level of output at minimum costs. Allocative efficiency can also be defined as a ratio between the total cost of producing a unit of output by employing actual relative amounts of inputs in a technically efficient way and the total cost of producing a unit of output using optimal relative amounts of inputs in a technically efficient way (Masuku et al., 2014).

### 2.1.3 Input- and output-oriented efficiency

According to Farrell (1957), economic efficiency can be measured taking into consideration two approaches, the input-oriented and output-oriented approach.

Input-oriented economic efficiency entails reducing the amount of input used without changing the quantity of output produced while output-oriented economic efficiency involves increasing the level of output without altering quantity of inputs used (Debertin, 1986). Input-oriented approach answers the question ‘by how much can the level of inputs be reduced without changing the quantity of output produced’, while output-oriented approach seeks to answer the question ‘by how can the output realised be increased in a proportionate manner without altering the quantity of inputs used’ (Maina, 2018).

#### 2.1.3.1. Input-oriented Technical efficiency and Allocative efficiency

Under the input-oriented measure, the unit isoquant shown in Figure 2.1 makes it possible to empirically determine the technical efficiency, TE. Following Coelli (1996) and assuming that output $y_1$ is produced using two inputs ($x_1$ , $x_2$), the unit isoquant of a fully efficient farm is represented by SS′. Any point outside the isoquant SS’ represents an unattainable point due to resource constraints. Point P defines the quantities of inputs $x_1$and $x_2$ utilised to produce one unit of output . The technical inefficiency of the farm is measured by the distance QP, which is the quantity by which all resources could be proportionally reduced without altering the quantity of output (ibid.). The technical efficient point is measured as 0Q/0P while the input-oriented measure of technical inefficiency is defined by QP/0P. A TE value of 1 indicates that the farm is fully technically efficient and zero otherwise (ibid.).

Input-oriented allocative efficiency, AE, can also be obtained in Figure 2.1. It measures how production costs can be reduced from an inefficient point so that the firm can operate on the allocatively efficient point, AA, which defines the isocost line (Coelli, 1996). The allocatively efficient point Q is defined by the ratio 0R/0Q for firm operating at point P (ibid.). The distance RQ represents the amount the production costs should be lowered for the farm to operate at both the technically and allocatively efficient point at Q′ rather than at the technically efficient but allocatively inefficient point Q. As indicated earlier, economic efficiency, EE, is the product of technical and allocative efficiency, and is defined by the ratio 0R/0P (ibid.). The distance RP represents the possible decrease in cost if the farm operates in an economically efficient way.

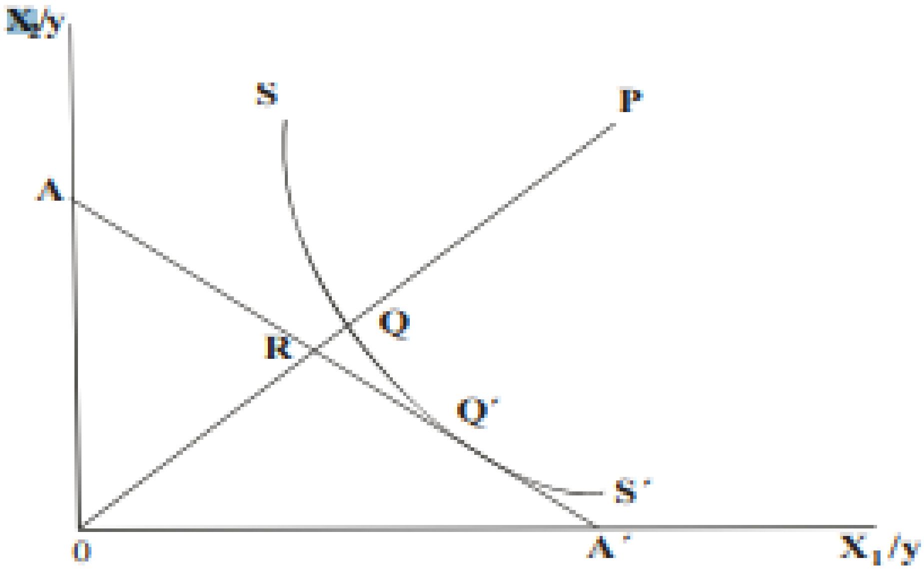


**Figure 2. 1. Input-oriented technical and allocative efficiency**

Source: Coelli (1996)

### 2. 1.3.2 Output-oriented technical efficiency and allocative efficiency

Figure 2.2 presents the output-oriented technical and allocative efficiency. Following Coelli (1996), and assuming that two outputs, $y_1$ and $y_2$,are produced using a single input, $x_1$, at constant return to scale, ZZ' represents a unit production possibility frontier. Point A is an inefficient firm as it lies below the production possibility frontier. The line AB defines technical inefficiency, as it shows the amount the output can be increased by, while the level of input remains unchanged. The output-oriented technical efficiency ratio is defined as 0A/0B. The output-oriented allocative efficiency is defined as 0B/0C. The overall output-oriented economic efficiency is defined as 0A/0C, which is the product of output-oriented technical and allocative efficiency.

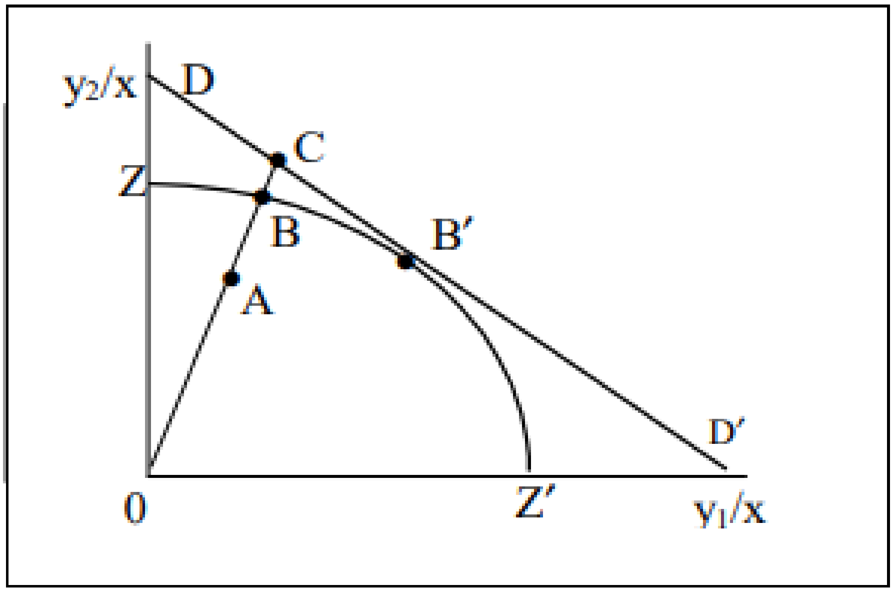


**Figure 2. 2. Output-oriented allocative efficiency and technical efficiency**

Source: Coelli (1996)

This study focused on output-oriented economic efficiency assuming that sorghum farmers in Botswana try to alter the quantity of sorghum produced rather than its input requirement set.

**2.2 Methods to assess economic efficiency**

Economic efficiency can be assessed using parametric and non-parametric methods. The main feature of parametric methods is the use of stochastic equations that separate the effects of random error and inefficiency (Fried et al., 2008). According to Khalad et al. (2016), non-parametric methods use linear programming techniques to measure the efficiency of decision makers.

The main non-parametric methods include the Data Envelopment Analysis (DEA) developed by Charnes et al. (1978), and the Free Disposal Hull method (FHD) developed by Deprins et al. (1984). The parametric method includes the Stochastic Frontier approach (SFA), the Thick Frontier approach (TFA), and the Distribution Free approach (DFA) (Weilli, 2004). The advantage of parametric over non-parametric methods is the ability of parametric methods to test hypotheses. However, parametric methods often suffer misspecification errors due to the requirements to specify a defined functional form for the production frontier and impose a distributional assumption on the inefficiency term (Theriault et al., 2014).

### 2.2.1 Parametric approach

Parametric methods use econometric modelling to construct an efficiency frontier (Asmare et al., 2018). As such, the parametric techniques require the specification of the functional form of the phenomenon of interest (e.g., either a cost or profit frontier) (Alrafadi, 2016). The main parametric techniques include the Stochastic Frontier Approach (SFA), the Thick Frontier Approach (TFA), and the Distribution Free Approach (DFA) (Weilli, 2004).

The SFA attributes the deviations from a cost or production function as due to random shocks and inefficiency components, which constitute two-sided distribution of the error term and a one-sided distribution of a non-negative inefficiency term (Asmare et al., 2018). The TFA differs from the SFA as it does not restrict on the distribution of the composite error term but assumes that the random error term represents deviations from predicted performance values (Berger and Humphrey, 1997). The DFA is used in panel data. It differs from the SFA in that it assumes the random errors tend to average out over time (Asmare et al., 2018). It also relaxes the distributional assumptions of the composite error term. All these approaches commonly suffer from specification errors because the specified profit or cost function is at best an approximation to the true (but unknown) counterpart (Irsova et al., 2010).

### 2.2.2 Non-parametric approach

The nonparametric method uses linear programming to measure the relative efficiency of a number of decision-making units through the identification of the optimal mix of inputs and outputs categorized based on their actual performance (Asmare et al., 2018). The DEA and the FDH are the main examples of non-parametric methods.

The DEA measures the efficiency of a decision-making unit relative to that of the whole sample using linear programming (Farrell, 1957). Initially proposed by Charnes et al. (1978) and extended by Banker et al. (1984), the DEA model consists of solving a fractional linear programming problem through an equivalent linear programming formulation assuming convexity and constant returns-to-scale (CRS) (Shiraz et al., 2014). The FDH, on the other hand, evaluates the technical efficiency of decision-making units without imposing the convexity assumption (Shiraz et al., 2014). It is a special case of the DEA model because it includes only the DEA vertices and the free disposal hull points interior to these vertices (Asmare et al., 2018). However, the FDH usually generates larger estimates of average efficiency than the DEA (Kumbhakar et al., 2000).

Both DEA and FDH methods allow efficiency to vary over time and do not impose any a priori functional form to the distribution of inefficiency scores (Asmare et al., 2018). However, non-parametric approaches have a major drawback of forcing all outputs to a frontier without accounting for random shocks and measurement errors that distort efficiency measurements (Ogundele et al., 2006). Due to the weaknesses of the non-parametric approach, this study used the parametric approach. In particular, the study used the SFA to assess the technical, allocative and economic efficiency of sorghum producers in Botswana. The choice of SFA was based on its ability to integrate both random shocks and inefficiency components besides its utility in hypothesis testing.

### 2.3 Stochastic Frontier Model

The stochastic frontier model was independently proposed by Aigner et al. (1977) and Meeusen et al. (1977). The econometric approach to estimate frontier models uses a parametric representation of technology along with a two-part composed error term. According to Aigner et al. (1977), the economic reasoning behind the specification of stochastic frontier model is that the production process is subject to two economically distinguishable random disturbances: random shocks represented by $v_i$ and a technical inefficiency term represented by $u_i$.

According to Asmare et al. (2018), stochastic frontier models differ depending on the nature of the dataset (either cross-sectional or longitudinal/panel). In cross-sectional stochastic frontier models, the inefficiency term, $u_i$, is constant over time while in panel data stochastic frontier models, it varies over time. On the other hand, for time-invariant data, the inefficiency term is time-invariant (Asmare et al., 2018). According to Mastromarco (2008), the random errors, $v_i$, are assumed to be symmetric and independently and identically distributed as N(0, $\sigma^2_v$) while the inefficiency term, $u_i$, is assumed to be independent of $v_i$ with a one-sided normal distribution $N^+(0, \sigma^2_u)$.

### 2.4 Empirical review on economic efficiency

Many studies have used the stochastic frontier to assess farmer efficiency using either cross-sectional or longitudinal/panel data. For example, Ogundari et al. (2007) examined the technical and allocative efficiency of smallholder cassava farmers in the Osun State of Nigeria using a stochastic production frontier and a cost function respectively.

The study found that cassava farmers were both allocative inefficient and technically inefficient, as mean efficiency was less than unity. The study found mean TE, EE and AE of 0.903, 0.89 and 0.807 respectively.

Zalkuwi et al. (2010) assessed the economic efficiency of maize production in Gonye Local Government Adamawa state in Nigeria using a stochastic cost function. The study established that the maize enterprise was profitable with a 113 percent return on per Naira invested. Age and farming experience reduced the cost inefficiency while literacy had a positive effect on cost efficiency.

Darko (2013) investigated the effect of farm input subsidy on economic efficiency of Malawi maize farmers using a stochastic frontier. The study found that the input subsidy improved farmers' technical efficiency by 47 percent. The study noted that input subsidy needed to be complemented by other government interventions such as irrigation.

Chiromo (2018) examined the impact of the farm input subsidy programme (FISP) and other determining factors on the technical, allocative and economic efficiency of smallholder maize farmers in Malawi using a stochastic frontier and a Tobit model. The study found an average technical and allocative efficiency of 61.3 and 66.9 percent respectively. The economic efficiency ranged between 14.1 and 74.6 with a mean of 59.2 percent reflecting substantial inefficiency. The study also observed a decreasing return to scale on maize production in Malawi. Subsidized farm inputs had no relationship with TE, AE and EE, which the study explained could be as a result of subsidy misuse. Farming experience, off-farm income, farmer's age and education were found to be significant drivers of farmer's technical efficiency. On the other hand, family size, distance to the market and farmer's marital status had a negative influence on technical efficiency.

Imoru (2015) assessed the effect of the fertilizer subsidy on technical efficiency of smallholder farmers in Ghana using stochastic frontier. A probit model was used to estimate factors determining success of participating in the subsidy programme. The study found that the efficiency of subsidy participants increased with use of subsidised fertilizer. The study also found that farm size, price of the subsidized fertilizer, distance to input markets and attempt at participating in the subsidy scheme influenced the probability to participate in the subsidy programme.

In North-Western Kenya, Mutoko (2008) evaluated the economic efficiency of smallholder maize producers using stochastic production and cost frontiers. The study found that 49 percent of respondents were economically efficient. In addition, economic efficiency was significantly influenced by off-farm income, family size, extension services, soil fertility management, credit and access to markets.

Djokoto (2012) assessed the technical efficiency of agriculture in Ghana using time series data and a stochastic frontier model. The study found a technical efficiency of 82 percent with a range of 59-96 percent. Labour had a positive effect on output, while land and seed had a negative effect on output. The agricultural sector experienced an increasing returns-to-scale of 1.74, suggesting that an increase in the output produced exceeded an increase in input use.

Pechrova (2015) assessed the impact of subsidies on the technical efficiency of farmers in the Liberecký region of Czech Republic using stochastic frontier analysis under a fixed-effects model. The study found a positive relationship between the direct and agri-environmental payments and inefficiency. The study also found that subsidies increased farmers' technical efficiency.

**2.5 Summary**

The preceding literature review shows that the method most widely used to assess farmers' economic efficiency is the stochastic frontier as it allows the integration of random shocks and the inefficiency component into a single composite error term. With regard to Botswana, no study was found to have assessed the effect of input subsidies on economic efficiency of sorghum producers, hence this study was undertaken to bridge the gap in knowledge. The study used the stochastic frontier method as it allowed for hypothesis testing.

# CHAPTER THREE: METHODOLOGY

## 3.1 Theoretical framework

The study is anchored on neoclassical theory of the firm in which firms are assumed to maximise profits under a budget constraint (Hart, 1989). In practice, however, firms frequently do not maximize profits due to either random statistical noise (e.g., due to market and production shocks) or their inability to optimize resource use (e.g., due to limited resource endowment, and low skills and knowledge sets, and failure to adopt efficient technology), or both (Farrell, 1957). The two (random statistical noise and failure to optimize) induce inefficiency in firms' production processes that is observed as differences in efficiency among producers **(**Kumbhakar, 1993). Technical inefficiency is the inability of the firm to produce at the production frontier given the input set, while the failure to optimize factors of production given their prices defines allocative inefficiency (Farrell, 1957). Therefore, the inability of firms to allocate the resources in an optimal manner to achieve maximum output leads to an increase in production costs and a decline in firm profits (Kumbhakar, 1993).

Aigner et al. (1977) developed a stochastic frontier that represents the sources of both technical and allocative inefficiencies. Accordingly, the error term, $\varepsilon_i$, is made up of two components: one (i.e., $u_i$) that accounts for inefficiency associated with the firm's inability to optimize output for a given level of inputs, and the other, $v_i$, that is due to random variation due to random shocks and errors in measurement. According to Coelli (2006), the stochastic frontier for the $i$th firm is specified as:

$$y_i = f(x_i, \beta)\exp(v_i - u_i) \ \forall i = 1,2,3 \dots N \qquad (3.1)$$

where $y_i$ is the possible output level of the $i$th firm, $f(x_i : \beta)$ is the suitable production function, $x_i$ is the vector of inputs used to produce $y_i$, $\beta$ is the vector of unknown parameters, $u_i$ is the technical inefficiency term, and $v_i$ is the random error term assumed to be independently, identically normally distributed and independent of $u_i$ with zero mean and variance $\sigma_v^2$ (i.e., $v_i \sim iid\ N(0, \sigma_v^2)$.The inefficiency term $u_i$ is assumed to be independently, identically and half-normal distributed with mean zero and variance $\sigma_u^2$, i.e., $u_i \sim iid\ N^+(0, \sigma_u^2)$.

The parameters of the stochastic frontier are usually estimated using the maximum likelihood estimator (MLE) because although the ordinary least squares (OLS) estimates are unbiased, consistent, efficient among linear estimators, the intercept is not consistent (Coelli, 1995). Hence, the MLE produces more efficient parameter estimates than the OLS with a consistent intercept and variance of the composite error, $(v_i - u_i)$ (Greene, 2017). Following Aigner et al. (1977), the log-likelihood function for the MLE is given as:

$$\ln L = K - I \ln \sigma + \sum_i \ln \Phi(\frac{\varepsilon_i \gamma}{\sigma}) - \frac{1}{2\sigma^2} \sum_i \varepsilon_i^2 \qquad (3.2)$$

where $\varepsilon_{i=} u_i + v_i$, $\sigma^2 = \sigma_u^2 + \sigma_v^2$, $\gamma = \sigma_u^2 / (\sigma_v^2 + \sigma_u^2)$, and $\Phi$= std normal cumulative distribution function. The likelihood function is expressed in terms of the variance parameters and sigma-squared (total variance); $\sigma^2 = \sigma_v^2 + \sigma_u^2$ where $\sigma_v^2$ is the variance of $v$ error and $\sigma_u^2$ is the variance of $u$ error. Both give the overall influence of all other factors not included in the estimation of technical efficiency (Greene,2017). The variance ratio gamma (γ) gives the proportion of total variation of the output from the frontier, which is explained by technical or allocative inefficiencies, i.e., $\gamma = \sigma_u^2 / \sigma_v^2 + \sigma_u^2$ (Greene, 2017). γ lies between zero and one, where zero indicates that the deviation from production efficiency are as result of random statistical noise only and one indicates that the deviation due to farmer's production inefficiency (Battese et al., 1995).

Two models are used to estimate the stochastic frontier shown in equation 3.1. These are the Battese and Coelli (1992) and Battese and Coelli (1995). The two models differ in that the latter simultaneously estimates firm's efficiency and inefficiency using a single step by expressing firm inefficiency effects $(u_i)$ as an explicit function of a vector of firm-specific variables and a random error (Batesse, 1995). The former model estimates the two aspects in two steps, thereby assuming independence of inefficiency effects. The Battese and Coelli (1995) specification was adopted in this study as it provides efficient results as it simultaneously estimates the kernel function and inefficiency model.

The estimation of equation 3.1 requires knowledge of the functional form of the deterministic kernel, $f(x_i, \beta)$. Indeed, Giannakas et al. (2003) point out that technical efficiency measures are extremely sensitive to the functional form of the underlying model. Various functional forms of the deterministic kernel have been suggested in empirical literature, the most popular being Cobb-Douglas and translog functions (Farrell, 1957).

The choice between the two is itself an empirical question and is usually guided by model tests such as the likelihood ratio test and Box-Cox transformation (Giannakas et al., 2003).

## 3.2 Empirical Framework

### 3.2.1 Estimating economic efficiency of sorghum producers in Botswana

#### 3.2.1.1 Choice of the deterministic kernel

The first stage of economic efficiency estimation involved the choice of appropriate models for estimating the deterministic kernel, $f(x_i, \beta)$, in equation 3.1. Because the empirical literature suggests the use of either a Cobb-Douglas or a translog functional form, the likelihood ratio (LR) test was used to choose the suitability of the two models in estimating economic efficiency, under the null hypothesis that the Cobb-Douglas model is the most appropriate functional form against the alternative in favor of the translog function (Mutoko, 2008). The calculated chi-square value for the LR for the production frontier was -2(39.5788 -50.2276) = 21.30, which was compared with the critical chi-square value of 11.0705 at 95 percent confidence level with 5 parameters (11 for translog) less 6 for the Cobb-Douglas), revealed that the critical value was less than the calculated chi-square value. Therefore, the null hypothesis that the Cobb-Douglas specification was the most appropriate functional form was rejected in favor of the translog. The LR calculated for the cost frontier was 11.965, while the chi square at 95 percent level of confidence was 7.815, the critical chi-square value was less than the calculated LR value hence, the null hypothesis of Cobb Douglas being the suitable functional form was rejected. The translog function was therefore the suitable functional form.

After choosing the functional form, the presence of technical or allocative inefficiency was tested using the LR test. The null hypothesis of the absence of technical inefficiency was rejected, implying the presence of technical inefficiency (see Appendix1). Similarly, the null hypothesis of the absence of allocative inefficiency was rejected implying presence of allocative inefficiency (see Appendix 2).

Following the selection of the most suitable functional form to estimate the deterministic kernel, the technical and allocative efficiency of sorghum producers were estimated using a stochastic translog production frontier and a stochastic translog cost frontier respectively. Economic efficiency was thereafter calculated as the product of technical and allocative efficiency scores based on Farrell (1957).

#### 3.2.1.2 Estimation of technical efficiency

Following Battese and Coelli (1995), the stochastic translog production function was specified as;

$$Iny_t = \beta_0 + \sum_i^4 \beta_1 \ln(x_{it}) + \frac{1}{2}\beta_2 (lnx)_{it}^2 + \frac{1}{2}\sum_{i=1}^4 \sum_{j=1}^3 \beta_3 \ln(x_{it}) \ln(x_{jt}) + (v_t - u_t) \tag{3.3}$$

where $y_t$is the natural logarithm of sorghum production per hectare in at time $t$, $x_t$ is the vector input quantities at time $t$ (ie., labour, number of tractors, seed quantity in tons, imported fertilizer quantity in kilogram). $(x_{it})^2$ represents input squared, $(x_{it})(x_{jt})$ represent interactions of inputs, $\beta$ is the vector of unknown parameters to be estimated, $t$ is the time period between 1998 and 2017, $v_t$ represents a normally distributed error term that is independent of $u_t$ and $u_t$ is the non-negative random variable which is assumed to be independently, identically and half-normal distributed with mean zero and variance $\sigma_u^2$, i.e., $u_i \sim iid\ N^+(0, \sigma_u^2)$.

The technical inefficiency model following Djokoto (2012) can be specified as;

$$u_{t=} \delta_0 + \delta_1 subdummy_t + \delta_2 edu_t + \delta_3 poli_t + \delta_4 trade_t + \delta_5 wea_t + \delta_6 rese_t + v_t \tag{3.4}$$

where $v_t$ is the error term defined as the positive truncation of the normal distribution with zero mean and variance $\sigma_v^2$ (Mutoko, 2008). The $\delta_i$ is a set of unknown parameters to be estimated while $subdummy_t$ is subsidy dummy with $\delta_1 = 1$, for the presence of input subsidy and zero otherwise, $edu_t$ is the average of number of years of formal schooling in Botswana at time $t$, $poli_t$ represents the political stability index at time $t$, $trade_t$ refers to trade openness defined as the ratio of the sorghum exports plus imports to Botswana's GDP, both in US$, at time $t$, $wea_t$ is rainfall variability at time $t$, and $rese_t$ is the percentage of agriculture GDP invested in agricultural research. Both the stochastic production function and the inefficiency model were estimated in a one-step procedure of Battese and Coelli (1995) using the maximum likelihood approach.

Table 3.1 presents the factors affecting the technical inefficiency of sorghum producers in Botswana and their expected signs.

**Table 3. 1. Factors influencing technical inefficiency of sorghum farmers in Botswana and their expected signs**

| Variable | Description | Units | Expected sign |
|---|---|---|---|
| Subsidy | Dummy | 0=Without subsidy<br>1=With subsidy | -/+ |
| Education | Mean years of formal schooling from primary to tertiary level | Years | - |
| Research | Ratio of GDP invested in agricultural research | Percent | - |
| Trade openness | Value imports +exports (US$ to GDP (US$) | Ratio | - |
| Political stability index | Index | None | - |
| Rainfall variability | Standard deviation of annual rainfall annually | None | + |

**Subsidy:** The variable was hypothesized to have a negative influence on technical inefficiency of sorghum producers in Botswana, hence increase technical inefficiency. The use of subsidy increase output due to increased access to input variables. Mustapha et al. (2016) found that access to subsidy increased technical inefficiency of farmers in Ghana, which was attributed to the administrative challenges in the distribution and accessing the input subsidy. Lachaal (1994) found that subsidies induced technical inefficiencies in dairy sector in America due to reduced motivation and efforts of milk producers.

**Education**: This variable was hypothesized to reduce the technical inefficiency of sorghum producers in Botswana; hence, a negative sign was expected. Educated personnel have more access to information and financial resources, which enhances technical efficiency. Chiona (2011) explained that education reduced the technical inefficiency of farmers in Zambia, as educated producers have increased access to financial institutions, market information and extension services. According to Pius et al. (2005), the education variable was significant in reducing technical efficiency in Nigeria, as educated farmers appreciate correct management practices and respond fast to new technologies.

**Research:** This variable was hypothesized to reduce technical inefficiency of sorghum producers in Botswana, investment in research formulates new technologies which increase output with less use of factors of production.

Fındık et al. (2015) evaluated the determinants of technical efficiency of software manufacturing firms in Turkey and found that research and development reduced the technical inefficiency of the firms. Liik et al. (2014) analysed the effect of research and development to the efficiency on the industry and sector level in OECD countries and found that research and development on capital had a large positive effect on highly technological industries. In Botswana, investment in agricultural research and development would lead to an increase in sorghum production efficiency, as new technology would be discovered that maximised output using less resources.

**Trade openness:** Ideally, trade openness would lead to an increased access to cheaper inputs, and increase output market between trading partners. The variable was hypothesized to reduce the technical inefficiency of sorghum producers in Botswana, as the more open the country is, the more access to cheaper inputs, and an increase in the output produced for exportation. Milijkovic et al. (2010) found that trade openness had a positive influence on technical inefficiency as it removed trade protectionism, which decreased the share of agricultural imports in agricultural GDP leading to an increase in technical efficiency. Hart et al. (2015) found that trade openness induced a negative impact on efficiency in the EU agricultural sector. However, trade openness reduced technical inefficiency in the long run as initial decrease in capital supply induced efficient use of other factors of production.

**Political stability index:** The political stability index was measured as political stability and absence of violence including terrorism, the measure of performance ranges between -2.5 and 2.5 for weak and strong governance performance respectively. It was hypothesized to have a negative relationship with technical inefficiency of sorghum farmers in Botswana, as a stable government ensure smooth running of business, hence producers are able to access inputs without fear of instability. Adkins et al. (2002) found that developing and developed economies countries with economic freedom due to political stability experience a reduction in technical inefficiency as the author established that institutions that ensures economic freedom promote efficiency. Prera (2012) estimated the relationship between technical efficiency and political instability and economic integration in Central America (Panama, Costa Rica, Honduras and Guatemala) and found that overall technical efficiency increased in Honduras, while Guatemala and Panama, technical efficiency increased after controlling for coups.

**Rainfall variability:** This variable was hypothesized to have a positive influence on the technical inefficiency of sorghum producers in Botswana, as the semiarid conditions of Botswana increases the chances of crop failures due to unreliable and varying rainfall. Deressa (2011) evaluated the effect of climatic and agro-ecological factors on productive efficiency of smallholder farmers in Ethiopia, and found that rainfall variability increased technical inefficiency during winter, while precipitation during summer and spring increased productive efficiency. Vigh (2018) found that rainfall increased the productive efficiency during seeding and vegetative periods of Hungarian arable farmers.

#### 3.2.1.3 Estimating Allocative Efficiency

According to Mutoko (2008), estimates from the cost frontier function have an error term different from that in the stochastic production function as $(u_i + v_i)$. The rationale for the difference in expression of the composite error term is that the minimum efficient cost frontier lies below the production cost of the firm (Mutoko, 2008). Therefore, the inefficiency component measures how much the observed production costs exceed the minimum efficiency cost bounded by the cost frontier.

Following Daglish et al. (2015), the Translog cost function equation was specified as;

$$ln\, c_t = \beta_0 + \beta_1 lny_t + \frac{1}{2}\beta_2 (lny)_t^2 + \sum_{i=1}^{4} \beta_3\, ln\, P_{it} + \frac{1}{2}\sum_{i=1}^{4} \sum_{j=1}^{3} \beta_4 lnP_{it} lnP_{ij} + \sum_{i=1}^{4} \beta_5 (lnP_{it})\,(lny_t) + (u_t + v_t) \qquad (3.5)$$

where $c_t$ is the total cost of production of sorghum in US$ at time $t, P_t$ is the vector of input prices (price of seeds, wage rate, price of tractors, and price of fertilizer in US$) at time $t$, $y_t$ is the output per hectare at time $t$, $\beta$ is the vector of unknown parameters, $v_t$ is the random error assumed to be independently distributed, and $u_t$ is the non-random error term which accounts for allocative efficiency.

The allocative inefficiency model based on Daglish et al. (2015) was specified as;

$$u_t = \delta_0 + \delta_1 subdummy_t + \delta_2 edu_t + \delta_3 poli_t + \delta_4 trade_t + \delta_5 wea_t + \delta_6 rese_t + v_t \qquad (3.6)$$

where $\delta$ is the unknown parameter and independent variables are as explained under technical inefficiency model.

Table 3.2 presents the factors influencing the allocative inefficiency of sorghum producers in Botswana and their expected signs.

**Table 3. 2. Factors influencing allocative inefficiency of sorghum producers in Botswana and their expected signs**

| Variable | Description | Units | Expected sign |
|---|---|---|---|
| Subsidy | Dummy | 0=Without subsidy<br>1=With subsidy | +/- |
| Education | Mean years of formal schooling from primary to tertiary level | Years | - |
| Research | Ratio of GDP invested in agricultural research | Percent | - |
| Trade openness | Value imports +exports (US$ to GDP (US$) | Ratio | - |
| Political stability index | Index | None | - |
| Rainfall variability | Standard deviation of annual rainfall annually | None | + |

Source: Author s' computation

**Subsidy**: This variable was hypothesized to have negative effect on allocative inefficiency of sorghum farmers in Botswana because the use of subsidies reduces input prices, hence lead to an increase in the use of the input variables. Hoque (1993) found that removal of input subsidy reduced allocative efficiency of smallholder's farmers in Bangladesh. Darko (2013) found that efficiency of maize farmers in Malawi increased with the amount of fertilizer subsidy.

**Education**: This variable was expected to have a negative influence on allocative inefficiency of sorghum farmers in Botswana, as education personnel are able to allocate resources optimally due to more access to price related information than their counterpart. Tijjani (2014) evaluated factors influencing allocative efficiency of rain-fed rice production in Nigeria, and found that education variable reduced the allocative inefficiency, as farmers with higher level of education tend to be more efficient in resource allocation. Rahman et al. (2012) found that education variable increased the resource allocation of rice producers in Bangladesh.

**Political stability index:** This variable was expected to reduce allocative inefficiency of sorghum producers in Botswana, as in a more political stable environment, firms are able to run their business smoothly without fear of instability, hence allocate their resources optimally.

Col et al. (2016) found that manufacturing firms in USA with greater exposure to political instability experiences a negative allocation of capital resources.

**Trade openness**: This variable was hypothesized to reduce allocative inefficiency of sorghum producers in Botswana, hence increase the level of allocative efficiency, due to more access to cheaper resources in a more open economy. According to Khan (2005), trade openness reduced the allocative inefficiency in Pakistan as more open economies grew rapidly, due to more access to cheap imported intermediate goods, larger markets and advanced technologies that contribute to efficiency. Bethou et al. (2015) examined the impact of international trade on aggregate productivity and resource misallocation, and found that trade openness had a negative effect on the allocation of labour of European countries.

**Rainfall variability:** This variable was hypothesized to have a positive effect on allocative inefficiency of sorghum producers in Botswana, as variability in rainfall leads to crop failure and crop losses. Farmers make decision which misappropriate the allocation of resources, in an environment where rainfall is unreliable and varying. Di Falco et al. (2009) investigated the effects of crop genetic diversity on production risk and farm productivity in the Ethiopia, and found that rainfall increases the allocative inefficiency as it affects farmers' decisions with respect to the use of productivity-intensifying external inputs and increases the risk of crop loss.

**Research**: This variable was expected to have a negative influence of allocation inefficiency of sorghum producers in Botswana and hence reduce the level of allocative inefficiency, it is through investment in agricultural research that better inputs and techniques are discovered at minimum costs, hence resources will be allocated optimally. Khaldi (1975) explained that research reduces allocative inefficiency of American farmers due to discovery of better technologies which reduces production costs faced by farmers, hence leading to an optimal allocation of resources given their prices.

### 3.2.1.4 Estimating economic Efficiency

A stochastic Translog production and stochastic translog cost function gave technical and allocative efficiency scores respectively which were then multiplied to give economic efficiency scores for years 1998 to 2017:

$$EE_t = TE_t X AE_t \tag{3.7}$$

where $EE_t$, $TE_t$ and $AE_t$ represent economic efficiency, technical and allocative efficiency of sorghum producers at time $t$ respectively.

### 3.2.2 Determining the effect of agricultural subsidies on economic efficiency of sorghum production in Botswana

Using the economic efficiency scores obtained in equation 3.7, a two-limit Tobit model was employed to evaluate the effect of the input subsidies on economic efficiency of sorghum producers in Botswana. The Tobit model was used because the efficiency scores ranged between 0 and 1. Under such circumstances, the OLS generates biased parameters.

The following Tobit model was specified:

$$EE_t = \delta_0 + \delta_1 subdummy_t + \delta_2 edu_t + \delta_3 poli_t + \delta_4 trade_t + \delta_5 wea_t + \delta_6 rese_t + \varepsilon_t \quad (3.9)$$

where $EE_t$ was the economic efficiency score that ranges between 0 and 1. All the other variables are as defined previously under the technical inefficiency model (equation 3.4).

Table 3.3 present factors influencing economic efficiency and their expected signs.

**Table 3. 3. Description of variables influencing economic efficiency of sorghum producers in Botswana and their expected signs**

| Variable | Description | Units | Expected sign |
|---|---|---|---|
| Subsidy | Dummy | 0=Without subsidy<br>1=With subsidy | + |
| Education | Mean years of formal schooling from primary to tertiary level | Years | + |
| Research | Ratio of GDP invested in agricultural research | Percent | + |
| Trade openness | Value imports +exports (US$ to GDP (US$) | Ratio | + |
| Political stability index | Index | None | + |
| Rainfall variability | Standard deviation of annual rainfall annually | None | - |

**Input subsidy**: The literature on the influence of input subsidies on economic efficiency is inconclusive.

For example, Lambarraa (2009) found that input subsidy had a negative effect on technical efficiency of Spanish olive farmers in Spain because it reduced farmers' motive to produce efficiently as farmers traded off market income for subsidy income. On the other hand, Seck (2017) found that subsidies lowered input prices and hence increased their usage, thereby improving farmers' efficiency in Senegal. Based on these studies, it was hypothesized that input subsidies would provide an incentive to farmers to produce sorghum more efficiently. Therefore, $subdummy_t$ was expected to be positively associated with economic efficiency in Botswana, as the presence of subsidy reduce the input costs leading to an increase use of the input, which increases the economic efficiency of sorghum producers in Botswana.

**Education**: The literacy rate was also expected to increase economic efficiency. Hence, a positive relationship between literacy rate and economic efficiency was expected, because education enhances knowledge, and informs the farmer on how to optimize production so as to generate more from use of inputs (Mohammed, 2012). The variable is often used as a proxy for human capital development. For example, Mutoko (2007) found that education increased the technical efficiency of maize producers in Kenya. Degefa (2014) found that better adoption of complex production technologies required technical knowledge and skills.

**Political stability**: Aisen et al. (2013) found that political instability reduced the economic efficiency by lowering the rates of productivity growth of 169 countries from 1960 to 2004. The study also found that it had an adverse effect on physical and human capital development human rights. As Rodrik (2000) suggests, institutions and the sense of democracy encourages stability, which may in turn lead to greater economic efficiency. In this study, therefore, political stability index, $poli_t$, was expected to have a positive effect on economic efficiency of sorghum producers in Botswana.

**Trade openness**: The trade openness is often associated with a reduction in imports and protectionism. Milijkovic et al. (2010) found that trade protectionism increased the efficiency of the agriculture sector in USA, as more open economies are expected to grow more rapidly through greater access to larger markets, cheap imported intermediate goods and advanced technologies that contribute to efficiency. According to Khan (2006), trade openness had a favourable influence on economic growth through increasing the productivity of Pakistan's economy. Based on these studies, it was expected that $trade_t$ would have a positive relationship with economic efficiency of sorghum production in Botswana.

**Rainfall variability**: The rainfall variability was expected to have a negative relationship with economic efficiency, because varying rainfall leads to an increase in risk of crop failure. According to literature agro-ecological factors are important factors that influence efficiency in production. Vigh et al. (2018) estimated the impact of climate factors on the technical efficiency of Hungarian arable farms, and found a positive relationship between rainfall and technical efficiency.

**Research and development**: The variable was hypothesized to be positively related to economic efficiency, because, educated personnel have skills and knowledge on the use and allocation of resources, which enhances economic efficiency of firms. According to Apokin et al. (2016), agricultural research had a positive effect of the level efficiency, as better technology is discovered through the use of research.

## 3.3 Research Design

The study used a deductive research design. According to O'Reilly (2009), deductive research formulates theory, uses existing theories to formulate a hypothesis followed by exploring empirical knowledge and data collected to test the established hypothesis. The deductive research design used in this study allowed the testing of the hypothesis that input subsidies have no effect on the economic efficiency of sorghum producers in Botswana.

## 3.4 Data Sources and Analysis

Secondary data were used in the study for the period between 1998 and 2017. A desk review was undertaken to gather data used in the analysis. The analysis of the data was undertaken using STATA 15. Table 3.4 presents a description of the data types used and their sources.

**Table 3. 4. Types of data and their respective sources**

| Data type | Description | Source of data |
|---|---|---|
| Yield | Sorghum output (Tons/hectare) | FAO/Ministry of Agriculture Botswana |
| Seed | Quantity of sorghum seed (ton) | FAO |
| Land | Land size (Hectare) | FAO/Ministry of Agriculture Botswana |
| Tractor | Number of tractors imported | FAO |
| Fertilizer | Quantity of fertilizer (kilogram) | Statistics Botswana |
| Labour | Manpower employed (Manpower/year) | International Labour Organization |
| Seed price | Average price of sorghum seed (US$/ton) | Statistics Botswana |
| Fertilizer price | Average price of fertilizer (US$/kg) | Statistics Botswana |
| Tractor price | Average price of tractor (US$/unit) | Statistics Botswana |
| Wage rate | Average price of manpower (US$/person/year) | Statistics Botswana |
| Subsidy | Government expenditure on input subsidies (US$) | Ministry of Agriculture Botswana |
| Education | Mean years of schooling (years ) | FAO |
| Political stability index | Index | World bank |
| Research and development | Percentage of GDP spent on agricultural R&D | Agricultural Science, Technology and Innovation |
| Rainfall | Rainfall variability | Botswana Department of Meteorology service |

## 3.5 Diagnostic Tests

### 3.5.1 Stationary test

This test was undertaken to determine whether the data were stationary. One of the OLS assumptions is that the variance and mean of random variables are constant over time. **(**Gujarati, 2009). The Augmented Dickey fuller (ADF) test (Dickey and Fuller, 1979) was used to test for stationary as it is the most commonly used in the literature. The null hypothesis was that the data were non-stationary against alternative of stationarity. The ADF test results (see Appendix 3) showed that all the input prices and total cost series were non-stationary, implying that OLS would give spurious parameter estimates. Accordingly, first differences were taken to achieve stationarity.

### 3.5.2 Autocorrelation

Autocorrelation was tested using the Durbin Watson test statistic (d) to check whether the series were serially correlated over time. In both cost and production functions, the Durbin Watson test found no evidence of autocorrelation (see Appendices 4 and 5).

### 3.5.2 Multicollinearity

Multicollinearity leads to regression coefficients remaining indeterminate with large standard errors so that independent variables become insignificant when they are supposed not to, i.e., leading to acceptance of zero null hypothesis (Gujarati, 2009). In this study, the Variance Inflation Factor (VIF) and partial correlation were used to test for multicollinearity. The results (see Appendix 6) showed that research, education and subsidy in the technical and allocative inefficiency model were collinear. In addition, the input variables and their prices were collinear in both the stochastic translog production and stochastic translog cost frontier respectively. Consequently, the sandwich estimator of White (1982) often known as the robust covariance matrix estimator was used to estimate both frontiers to ensure consistent parameter estimates.

### 3.5.3 Heteroscedasticity

According to Gujarati (2009), heteroscedasticity is present when the disturbance terms do not have a constant variance. This renders the estimators to no longer have minimum variance, hence the confidence intervals, the $t$ and $F$ tests computed are no longer reliable. The Breusch Pagan–Godfrey test was used to test for heteroscedasticity. The results showed no evidence of heteroscedasticity in both production and cost functions (see Appendix 7).

# CHAPTER FOUR: RESULTS AND DISCUSSION

## 4.1 Characterization of sorghum production in Botswana

### 4.1.1 Some summary Statistics

Table 4.1 presents the summary statistics of sorghum production in Botswana. There was high variation in the labour employed in sorghum production. The increase could be attributed to the increase in the number of farmers as the ISPAAD Programme was implemented in 2008. The number of farmers involved in crop production increased from 31,000 farmers to 118,000 farmers between 2008 and 2011 (Marumo et al., 2014). Therefore, there was an increased demand for labour, hence reallocation of the labour to sorghum production.

**Table 4. 1. Descriptive statistics of sorghum production in Botswana**

| Variable | Mean | SD | Minimum | Maximum |
|---|---|---|---|---|
| Sorghum output (Ton) | 22,033.1 | 8,105.3 | 10,231 | 35,508 |
| Yield (Ton/ha) | 0.7 | 4.79 | 0.16 | 1.83 |
| Seed (Ton) | 1,097.1 | 387.3 | 150 | 1,500 |
| Labour (Man/year) | 31,841.8 | 46,915.4 | 5,750 | 219,000 |
| Land (Hectares) | 39,851.5 | 16,681.6 | 10,000 | 72,000 |
| Tractor (Quantity) | 5,957.4 | 13,412.6 | 134 | 57,928.2 |
| Fertilizer (Kg) | 10,251.1 | 8,326.8 | 141.4 | 25,305.7 |
| Tractor price ($/unit) | 5,822 | 7,015.1 | 61.4 | 5,872.4 |
| Seed price ($/ton) | 173.6 | 66.5 | 96 | 304 |
| Wagerate ($/person/year) | 1,842.6 | 381.9 | 876 | 2,232 |
| Fertilizer prices ($/kg) | 94.0 | 134.3 | 6.8 | 538.4 |
| Political index(Units) | 0.916 | 0.1 | 0.8 | 1.1 |
| Trade openness ratio | 0.0018 | 0.00295 | 0.00 | 0.01 |
| Mean education (Years) | 8.5 | 0.5 | 7.6 | 9.3 |
| Rainfallvariability(d) | 33.8 | 7.8 | 20.6 | 47.0 |
| Research investment (% of GDP) | 3.9 | 1.5 | 2.1 | 7.4 |
| Total subsidies($) | 4 ,255,688.6 | 3,830,120.0 | 0.0 | 16,306,050 |

Source: Author s' computation

As shown in Table 4.1, the price of a tractor ranged from a low of US$61.4 to a high of US$ 5,872.4, leading to a variation of US$ 7,015.1. This disparity between minimum and maximum prices was due to an increase demand for tractors**.**

The results are in agreement with the results of Civilek (2016) who explained that the demand for tractor use increased by 34 percent, therefore this can lead to a variability of price of tractors**.** The variation in tractor use was 13,412.6 units, which could be as a result of increased demand for tractors when ISPAAD was launched in 2008.

The average sorghum yield was 0.7 ton/ha, which is way below its potential of one MT /ha and 2.5 ton/ha for subsistence and commercial farmers respectively (Statistics Botswana,2015). On the other hand, the average total sorghum output of 22,033 MT is way below the potential output of 100,000 MT recorded between 1979 and 2015 (FAO, 2017). The comparative sorghum average yield and output for South Africa is 2.85 MT/ha and 530,000 MT/year respectively. The output produced ranged between 155,000 to 375,000 tons, while the yield produced ranged between 2.2 ton/ha and 3.5 ton/ha (Schulze, 2007). This means sorghum productivity is low as compared to South Africa, largely due to poor agro-climatic conditions in Botswana.

### 4.1.2 Trend of sorghum yield

Figure 4.1 presents the trends of sorghum yield and rainfall experienced in Botswana between 1998 and 2017. In general, sorghum yield has remained constant over time as illustrated by the almost flat trend line, because of poor agro climatic conditions. Chipanshi et al. (2003) explained that sorghum productivity is low due to poor soils and highly dependent on varying and low rainfall. The yield realized increased between 2009 and 2011, due to an increase in rainfall levels during the same period. Before the introduction of ISPAAD sorghum yield was increasing most times, however upon introduction of ISPAAD in 2008, sorghum yield was declining most times.

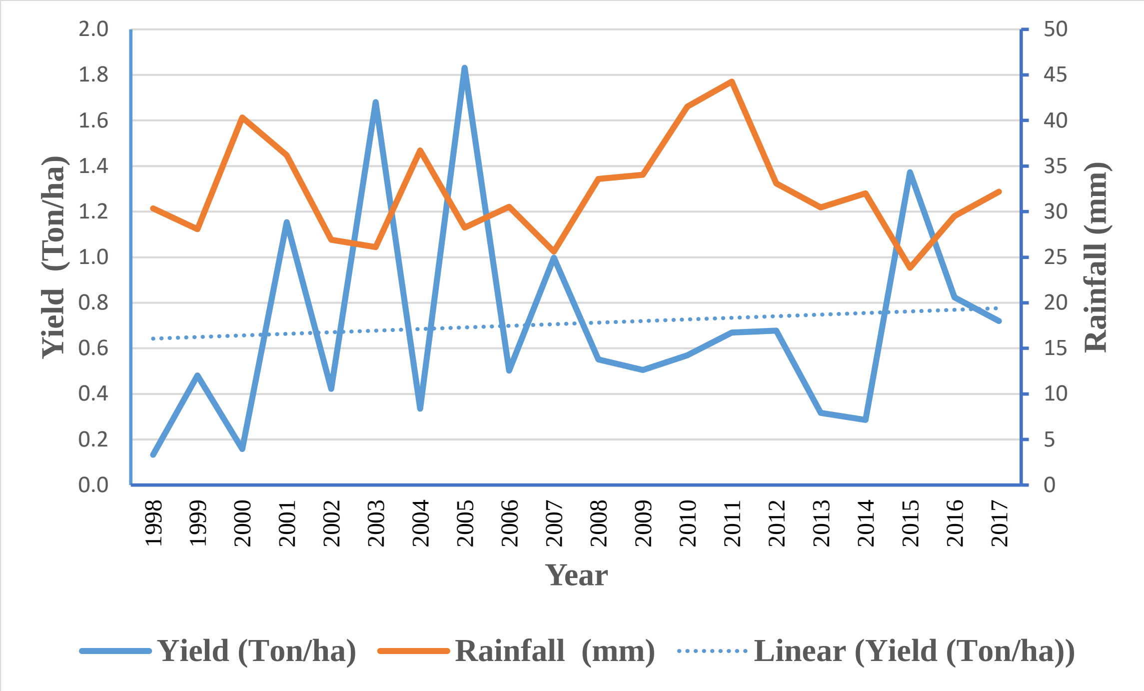


**Figure 4. 1. Trend of sorghum yield and rainfall in Botswana between 1998 and 2017**

### 4.1.3 Trend of sorghum production

Botswana's sorghum output increased steadily between 1998 and 2017 (Figure 4.2) as depicted by the trend line. The output increased between 2009 and 2010, because of an increase in the rainfall level between the same period. The output level was declining before the introduction to ISPAAD, with the introduction of the ISPAAD, the output level rose between 2009 and 2011, which could be attributed to an increase in the usage of inputs, as its prices were subsidized.

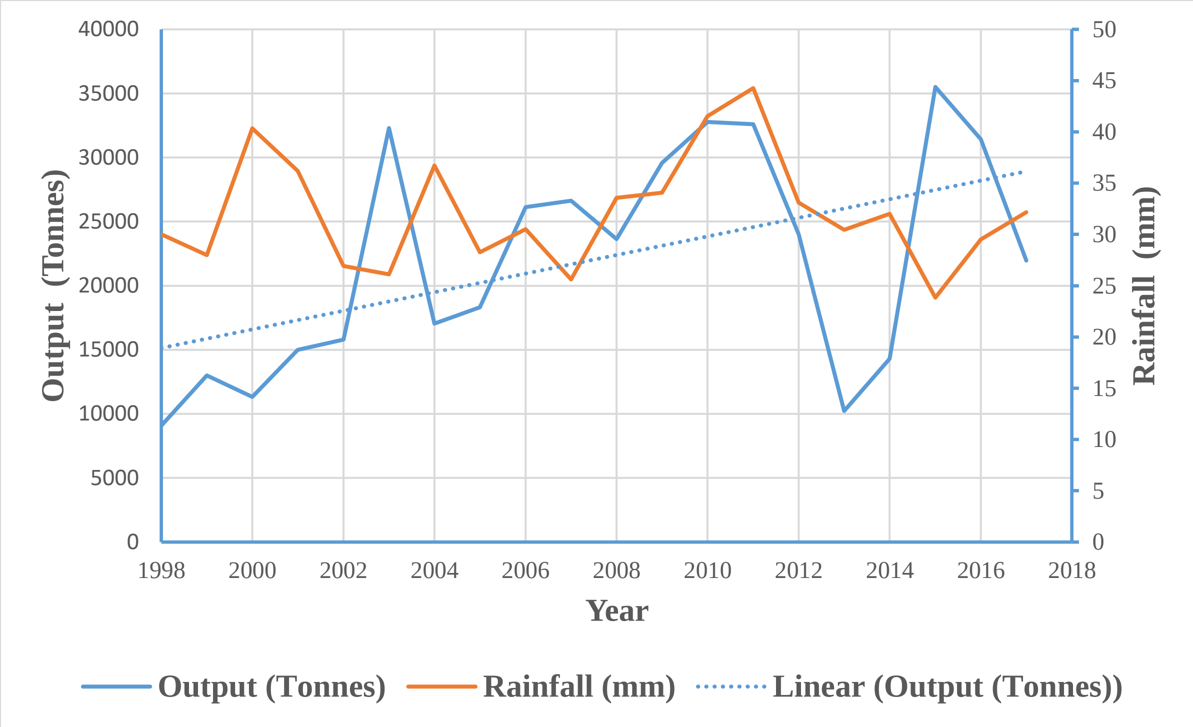


**Figure 4. 2. Trends of sorghum output and rainfall in Botswana between 1998 and 2017**

### 4.1.4 Trend of input prices

The prices of all sorghum inputs (seeds, fertilizer, labor and tractors) rose steadily over the study period (Figure 4.3). However, all prices expect seed prices experienced considerable variability probably due to increase in demand for sorghum seed, induced by an increase demand for food grains. Seed prices increased throughout the study period perhaps due to an increase demand for sorghum usage as food and animal feed. Bhagavatula et al. (2013) found that the prices of sorghum increased during period between 2001 and 2007, which the current studies cover, due to an increase demand for sorghum. On the other hand, fertilizer prices had a sharp increase between 2010 and 2013. Rude et al. (2013) attributed the rise in price of imported fertilizer in America to an increase in demand for food grains, which induced an increase in the demand for fertilizers. The author further explained that import fertilizer price increased by 466.2 percent between 2002 and 2012 due to an increase in price of food grain prices and price of natural gas.

After a sharp decline between 1998 and 2000, the wage rate recovered in 2001 but at a low rate probably due to availability of unskilled labour forces in the sorghum sector. Reddy (2015) attributed the slow growth of wage rate in the agricultural sector than other sector in India to low literacy rates

. Finally, tractor import prices experienced a sharp increase between 2007 and 2015 because of increase price of fuel and increase demand for tractor use. Civilek (2016) found that the demand for tractor in Turkey had increased by 34 percent for the past 10 years, therefore an increase in demand for tractor increases the price of tractors.

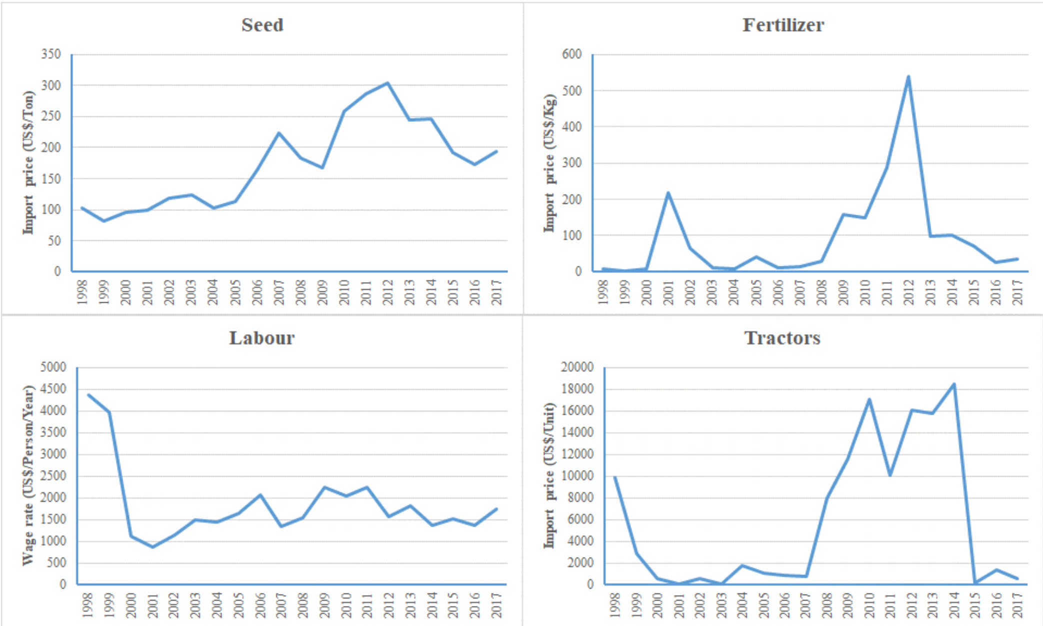


**Figure 4. 3. Trends of sorghum input prices in Botswana between 1998 and 2017**

### 4.2 Factors influencing technical efficiency of sorghum production in Botswana

Table 4.2 presents the results of the estimation of the stochastic production frontier incorporating the technical inefficiency model in a single step following Batesse and Coelli (1995). The results of the Cobb-Douglas production function are presented for comparative purposes only and are not discussed further. Due to stability issues of the Translog function as a result of limited sample size of 20 observations (covering 20 years of annual data) for the production function, some interaction terms were not included in the model.

The value of gamma was 0.999 implying that 99.9 percent of the variation in total output was explained by the technical inefficiencies. The value of sigma-squared was 0.0004 and significant at 5 percent. According to Wigner et al. (1997), the statistical significance of the sigma-squared is an indication of a good fit of the model and it verifies the distribution assumption of the composite error term. The translog model was statistically significant as shown by the statistically significant Wald chi-square values of 207.25 at 5 percent level.

**Table 4. 2. Maximum likelihood estimates of Cobb-Douglas and translog stochastic production frontier of sorghum producers in Botswana**

| | **Translog** | | | **Cobb-Douglas** | | |
|---|---|---|---|---|---|---|
| **Variable** | **Coefficient** | **SE** | **Z** | **Coefficient** | **SE** | **Z** |
| Lnlabour | -0.961 | 0.398 | -2.41** | -0.030 | 0.020 | 1.47 |
| Lnseed | -1.300 | 0.696 | -1.85* | 0.024 | 0.009 | 2.81** |
| Lnfertilizer | 0.178 | 0.228 | -0.78 | -0.005 | 0.010 | 0.45 |
| Lntractor | -0.236 | 0.142 | -1.67* | 0.007 | 0.009 | 0.79 |
| Time trend | -0.008 | 0.004 | -2.19** | 0.0003 | 0.004 | 0.07 |
| Lnseed*Lnfertilizer | 0.002 | 0.240 | 0.08 | | | |
| Lnlabour*Lnseed | 0.130 | 0.051 | 2.56** | | | |
| Lntractor*Lnlabour | 0.006 | 0.013 | 0.45 | | | |
| Lnfertilizer*Lnfertilizer | 0.010 | 0.005 | 2.08** | | | |
| Lntractor*Lntractor | 0.012 | 0.002 | 5.50*** | | | |
| Constant | 11.970 | 5.702 | 2.10** | 1.091 | 0.263 | 4.15*** |
| **Inefficiency model** | | | | | | |
| Lneducation | -1.064 | 0.379 | -2.81** | 0.100 | 0.040 | -2.46** |
| Lntradeopeness | 0.040 | 0.052 | 0.77 | 0.019 | 0.019 | -0.99 |
| Lnresearch | 0.015 | 0.189 | 0.08 | -1.038 | 0.049 | 21.3*** |
| Lnrainfallvariability | 0.009 | 0.021 | 0.42 | 0.421 | 0.071 | 1.59* |
| Subsidy dummy | | | | -0.466 | 0.116 | 0.41*** |
| Constant | 2.506 | 0.765 | 3.28*** | 0.601 | 0.364 | 1.65* |
| Lambda | 0.033 | 0.003 | 10.27*** | 0.031 | 0.006 | 5.02 |
| u_sigma | 0.0006 | 0.0004 | 1.64* | 0.001 | 0.0006 | 1.77* |
| v_sigma | 0.020 | 0.003 | 6.19*** | 0.033 | 0.006 | 5.18*** |
| Log likelihood | 50.2276 | | | 39.5788 | | |
| Wald chi2(10) | 207.25 | | | 75.96 | | |
| Prob > chi2 | 0.0000 | | | 0.0000 | | |
| Gamma | 0.999 | | | | | |
| $Sigma^2$ | 0.0004 | | | | | |

***, **, * denote significance at 1%, 5% and 10% levels respectively

Based on Table 4.2, in the translog production function, labor, seed and tractor negatively influenced sorghum yield in Botswana over the study period. This implies that a rise in the use of the three inputs would lead to a reduction in yield.

A one percent increase in seed and tractor use led to a decrease in yield by 1.3 and 0.24 percent respectively at 10 percent level of significance. According to Mutoko (2008), the negative relationship between output and factors of production indicates that the input use is at its maximum level. Hence, more application of such an input beyond the current level will lead to fall in output as is characteristic when operating in stage III of the classical production function where the marginal product is zero or even negative (Debertin, 2012). Therefore, the negative coefficients on labor, seeds and tractor depict the law of diminishing returns where additional use of a variable input leads to a decrease in additional output. The sum of elasticity was 0.0037, which shows that the production realized was operating under decreasing returns-to-scale. The time trend is also negative suggesting that sorghum yield declined over time. This could be because sorghum production was reduced as a result of unreliable rainfall in Botswana. Bi et al. (2007) also found that yield declined in Chinese-fir plantation due to a decline in soil fertility. Chipanshi et al. (2003) attributed the reduction in the yield of maize and sorghum in Botswana to climate change.

The interaction between seed and labour had a positive effect on sorghum yield at 5 percent significance level in the translog function. Therefore, a one percent increase in both inputs would increase sorghum yield by 13 percent, *ceteris paribus*. Although fertilizer alone had no effect on sorghum yield, its square had a positive effect. Likewise, tractor alone had a negative effect on yield but a positive one when squared. The significance of the squared variables show that the variables have a positive relationship with sorghum yield implying that the increase use of input variables would enhance the yield realized. The results on the insignificant effect of fertilizer on yield, while the squared fertilizer was significant are similar to Mutoko's (2008) who explained that the insignificance of unsquared terms implies that current levels are at sub-optimal levels and that increasing input use would lead to higher yields (Table 4.2). Hasnain et al.'s (2005) who reported a positive relationship between rice production and irrigation squared in Bangladesh, they explained that an increase in using irrigation would increase rice output at an increasing rate.

In the inefficiency model in Table 4.2, only the mean of years of schooling was statistically significant implying that education increased the technical efficiency of sorghum producers in Botswana. Studies show that the adoption of complex production technologies requires technical knowledge and skills which come with education. This is because educated producers may have better access to marketing information, extension services, and financial information.

Besides, education is a proxy for human capital development and as the results show, potentially enhances farmers' technical efficiency This finding tallies with that of Mutoko (2008) who observed that education level reduced technical inefficiency of maize producers in Kenya. The result is also in line with that of Chiona (2011) in Zambia where formal education increased the technical efficiency of maize farmers.

**4.3. Factors influencing allocative efficiency in sorghum production in Botswana**

Table 4.3 presents the parameter estimates of both Cobb-Douglas and translog cost functions for factors influencing sorghum farmers' allocative efficiency. The results of the Cobb-Douglas production function are presented for comparative purposes only and are not discussed further. Due to stability issues of the Translog function as a result of limited sample size of 20 observations (covering 20 years of annual data) for the cost frontier, some interaction terms were not included in the model. The value of gamma in translog cost function was 0.17, indicating the model explained only 17 percent of total variation in the cost function are due to allocative inefficiency. The fact that sigma-squared was 0.25 and was significant indicates a good model fit. The Translog model was significant as shown by the Wald chi-square value of 89.52 (p=0.05) function.

The results of the translog cost function show that yield, time trend and price had a statistically significant influence on the total cost of sorghum production in Botswana between 1998 and 2017. A one percent increase in yield would lead to a 4.91 percent reduction in total costs. In other words, the marginal costs of producing an extra unit of output reduces. This finding is similar to Srivastava's (2017) who observed an inverse relationship between yield and total production costs of cereals, oilseeds, cotton and pulses in India. The author explained that this was due to yield improvement through technological interventions which absorb the rising cost of crop production.

The positive sign on the trend suggests that the total cost of sorghum production in Botswana increases with time. Thus, an extra year of sorghum production would increase total costs by 0.182. This could be due to the increase in the prices of factors of production such as labour as following increased demand after the introduction of ISPAAD. Liu (2015) found similar results, as the author explain that production costs of sweet sorghum were increasing in the Wuyuan in China because of high labour costs.

**Table 4. 3. Maximum likelihood estimates of Cobb-Douglas and Translog cost frontier functions of sorghum production in Botswana**

| | Translog | | | Cobb-Douglas | | |
|---|---|---|---|---|---|---|
| **Variable** | **Coefficient** | **SE** | **Z** | **Coefficient** | **SE** | **Z** |
| Lnyield | -4.908 | 2.020 | -2.43** | -4.756 | 1.964 | -2.42** |
| Time trend | 0.182 | 0.064 | 3.91*** | 0.051 | 0.209 | 2.46** |
| Lndwagerate | 1.400 | 0.375 | 3.56*** | 1.433 | 0.294 | 4.87*** |
| Lndtractorprice | | | | 0.084 | 0.045 | 1.84* |
| Llndfertilizerprice | | | | -0.151 | 0.121 | -1.24 |
| Lndseedprice | 0.867 | 0.405 | 2.14** | | | |
| Lndwagerate*Lndwagerate | 0.335 | 1.014 | 0.33 | | | |
| lnwagerate*Lnseedprice | 6.456 | 2.216 | 2.91*** | | | |
| Lndtractorprice*Lndwagerate | 0.621 | 0.679 | 0.91 | | | |
| Lndtractor*Lndfertilizer | 0.155 | 0.056 | 2.76*** | | | |
| Constant | 2.005 | 2.112 | 0.95 | 3.601 | 1.744 | 2.06** |
| ***Inefficiency model*** | | | | | | |
| Lneducation | | | | 3.262 | 5.378 | 0.61 |
| Subsidy dummy | 0.309 | 0.212 | -1.46 | -2.374 | 1.932 | -1.23 |
| Lntradeopeness | 1.250 | 0.470 | 2.66*** | 1.174 | 0.068 | 1.73* |
| Lnrainfallvariability | 2.277 | 0.872 | 2.61*** | | | |
| Constant | 2.334 | 4.671 | 0.50 | 1.720 | 9.158 | 0.19 |
| Lambda | 2.185 | 0.188 | 11.61*** | 1.993*** | 0.397 | 5.01*** |
| U_sigma | 0.457 | 0.149 | 3.07*** | 0.606 | 0.346 | 1.75* |
| Log likelihood | -7.1762 | | | -13.1587 | | |
| Wald chi | 89.52 | | | 85.92 | | |
| Prob > chi2 | 0.0000 | | | 0.0000 | | |
| V_sigma | 0.209 | 0.065 | 3.23*** | 0.303 | 0.085 | 3.85*** |
| Gamma | 0.17 | | | | | |

Source: Author’s computation

***, **, * denote significance at 1%, 5% and 10% levels respectively

As expected, input prices increased the total cost of sorghum production. Accordingly, a one percent increase in the wage rate, seed price, and wage and seed and tractor and wage interactions would all increase the total cost of sorghum production by 1.4, 0.87, 6.45, 0.62 and percent respectively (Table 4.3). These findings tally with that of Ogundari et al. (2007) who observed that wage rate, cost of labour, and prices of planting materials, agro-chemicals and farm tools increased total cost of cassava farmers in Nigeria. Abdulai et al. (2017) also found a positive relationship between input prices and total costs of maize farmers in Ghana. Mbanasor et al. (2008) also found a positive relationship between input prices and total cost, as the study found that price of agro chemicals, land rent, wage rate and price of planting materials increased the total costs of commercial vegetable producers in Akwa Ibom state in Nigeria. Okoye et al. (2007) also found that wage rate, price of fertilizer, land rent, and the price of manure increased the total cost of smallholder cocoyam farmers in Anambra state in Nigeria.

Contrary to expectations, trade openness had a positive and significant influence on allocative inefficiency in the translog model at 1 percent level of significance, implying that it increased sorghum producers' allocative inefficiency. This is surprising given that the more open the economy is, the more access to productive resources its producers become. The positive effect of trade openness on sorghum farmers' allocative inefficiency could perhaps be attributed to competition from more efficiently produced sorghum imports from South Africa. Bai et al. (2019) found similar results and explained that more open trade induced a misallocation of resources in the manufacturing industry in China due to less inefficient firms expanding their output than more productive ones. Therefore, the negative effect could be due to the sorghum industry being more import-based hence creating misallocation of resources by local farmers probably due to low demand for local sorghum.

The positive relationship between weather variability and allocative inefficiency among sorghum producers in Botswana was expected *a priori*. It reflects the increase in production risk as rainfall becomes more variable, which leads to a rise in farmers' on-farm resource misallocation. Di Falco and Chavas (2009) found that rainfall variability influenced farmers' decisions regarding the use of productivity-enhancing external inputs, which imposed *ex ante* barriers to input use, thereby increasing crop losses in Ethiopia.

### 4.4 Determinants of economic efficiency in sorghum production in Botswana

#### 4.4.1 Summary statistics of technical, allocative and economic efficiency

Economic efficiency scores were calculated by multiplying TE and AE scores obtained from the translog production and cost functions respectively. Notably, none of the efficiency scores reached unity indicating that Botswana sorghum producers were both technically and allocatively, and hence, economically inefficient between 1998 and 2017. As shown in Table 4.4, sorghum producers' mean technical, allocative and economic efficiency scores were 0.94, 0.67 and 0.64 respectively. This implies that sorghum producers would need to expand production by 6 percent but reduce production costs by 33 percent to respectively operate on the efficient production and cost frontiers. In addition, sorghum producers needed to save 37 percent on total production costs to be economically efficient. These results tally with those of Tukela et al. (2013) who observed a mean technical efficiency score of 0.72 for maize farmers in Ethiopia. In Malawi, Tchale (2009) found that the allocative inefficiency of maize farmers worse than their technical inefficiency, which corresponds with the findings of this study. Tchale (2009) attributed the low overall economic efficiency to cost inefficiency.

**Table 4. 4. Summary statistics of technical, allocative and economic efficiency of sorghum producers in Botswana**

| Variable | Mean | Std | Min | Max |
|---|---|---|---|---|
| TE | 0.94 | 0.064 | 0.6994 | 0.9999979 |
| AE | 0.67 | 0.317 | 0.06 | 0.9637 |
| EE | 0.64 | 0.314 | 0.05 | 0.9638 |

Source: Author's computation

TE-Technical efficiency    AE-Allocative efficiency    EE- Economic efficiency

#### 4.4.2 Trend of technical, allocative and economic efficiency

Figure 4.4 presents the trend of technical, allocative and economic efficiency of sorghum production in Botswana between 1998 and 2017. Both technical and allocative efficiency scores fluctuated widely together with the best years being 2015 with a 0.9637 allocative efficiency score and 2016 with 0.9999979 technical efficiency score. The economic efficiency scores also fluctuated over the same period but less than both technical and allocative efficiency. As indicated earlier, none of the 20 years had an efficiency score of one. This implies that in all the years under study, sorghum farmers in Botswana were economically inefficient.

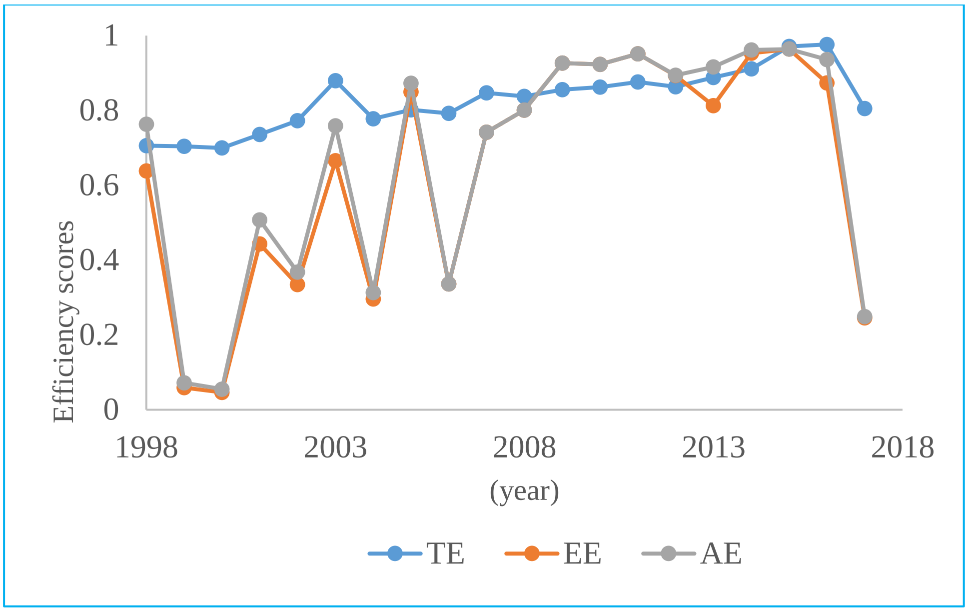


**Figure 4. 4. Trends of technical, allocative and economic efficiency scores of sorghum producers in Botswana between 1998 and 2017**

### 4.4.3 Effect of input subsidies on economic efficiency of sorghum producers in Botswana

Table 4.5 presents the Tobit model results of factors influencing economic efficiency of sorghum producers in Botswana. The model goodness of fit was calculated using the log-likelihood ratio test (Maddala, 1983):

$R^2 = 1 - [\exp(-2(lm \; - ln/N))]$

where the log-likelihood of the restricted model (ln) was -3.511 while that of the unrestricted model (lm) was 14.608. The number of observations was 20 years giving a pseudo $R^2$ of 0.82, which shows a good fit of the model into the data. Out of the six regressors in the model, only four were statistically significant; i.e., rainfall variability, political stability index, trade openness and input subsidy dummy. Investment in research and education variables were insignificant in affecting the economic efficiency of sorghum producers in Botswana.

As expected *a priori*, rainfall variability was negatively associated with economic efficiency of sorghum producers which can be attributed to increased production risk that increases the probability of crop failure. Thus, a one percent increase in rainfall variability would reduce the economic efficiency of sorghum producers by 27 percent. According to Hansen et al. (2011), low agricultural productivity in many SSA countries is attributable to their heavy reliance on rain-fed production, which is often variable over time and space. Amare et al. (2018) reported rainfall variability reducing agricultural productivity in Nigeria by 38 percent.

**Table 4. 5. Tobit model parameter estimates of the effect of input subsidies on economic efficiency of sorghum producers in Botswana**

| Variable | Coefficient | Marginal effect | Std. Err. | T-value |
|---|---|---|---|---|
| Log education | 0.114 | -0.114 | 0.152 | -0.14 |
| Log rainfall variability | -0.273 | -0.272 | 0.131 | -2.07* |
| Log investment in ARD | -0.071 | -0.071 | -0.470 | -2.67 |
| Subsidy dummy | 0.286 | 0.286 | 0.129 | 2.22** |
| Log political stability index | 1.022 | 1.023 | 0.426 | 2.40** |
| Log trade openness | -0.191 | -0.191 | 0.026 | -7.28*** |
| Constant | 0.419 | | 1.947 | 0.21 |
| F(6,14) | 36.91 | | | |
| Prob > F | 0.0000 | | | |
| Log likelihood | 14.068 | | | |

Source: Author's computation
*****, **,** * denote significance at 1%, 5% and 10% levels respectively

As expected *a priori*, the input subsidy dummy was positive and statistically significant at 5 percent level, implying a positive effect on the economic efficiency of sorghum producers in Botswana over the study period. This could be because input subsidies reduce the prices paid by producers to procure inputs, thereby allowing them to increase the amount of input purchased and applied in production. Accordingly, the shift from no input subsidies to having input subsidies would increase the economic efficiency of sorghum producers in Botswana by 28.6 percent. This finding tallies with that of Nasrin et al. (2018) who observed that economic efficiency increased with use of subsidized fertilizer in Bangladesh. Seck (2015) also made a similar finding in Senegal. The author attributed increased economic efficiency to the input subsidies provided farmers, which subsequently translated to increased output. Denning et al. (2009) also found a positive effect of input subsidies on the technical efficiency of maize farmers in Malawi.

The political stability index had a positive influence on sorghum producers' economic efficiency at five percent significance level as expected. This implies that the stable political environment in Botswana enhanced the economic efficiency of sorghum producers, perhaps due to a good administrative environment that reduced the political risk in the country.

Accordingly, a one percent increase in the political stability index increased the sorghum producers' economic efficiency by 1.02 percent. Aisen et al. (2013) found that political instability limits growth by reducing the physical and human accumulation, as well as the rates of productivity growth, and hence reduces economic efficiency.

Finally, trade openness had a negative but significant effect on sorghum producers' economic efficiency, contrary to *a priori* expectation. Ideally, trade openness is expected to increase economic efficiency through spill-over effects of technology transfer and mobility of capital and labor, which enhances efficiency as observed by Choartareas et al. (2003). The negative effect of trade openness could be a result of the sorghum industry being an import-based such that the local farmers are economically inefficient due to competition from its neighbouring exporting firms. Accordingly, a one percent increase in trade openness index would reduce the economic efficiency of sorghum producers by 19 percent. Funtes (1995) found contradicting results; namely, trade openness enhanced economic efficiency of manufacturing industry in Chile due to more competition from internal firms and significant reduction in costs as the industry was more export-based. Therefore, the contradicting results by the current study could be due to the fact that there is more competition from efficient exporting farmers mainly from South Africa. The result of this study is however supported by Bai et al. (2019) who explained that more open trade induces a misallocation of resources because of competing firms who can be able to monopolize the sorghum industry because of their economies of scale. In the case of Botswana, the negative effect could be due to the fact that the sorghum industry relied more on imports from South Africa, whose competition causes Botswana producers to lack adequate market for their produce due to low demand.

### 4.5 Hypothesis testing

In Section 1.4, it was hypothesized that the technical, allocative and economic efficiency scores of sorghum producers would be less than unity, i.e., that producers would be inefficient. Because the average technical, allocative and economic efficiency scores were 0.94, 0.67 and 0.64 respectively and therefore less than unity, we fail to reject the null hypothesis and conclude that sorghum farmers in Botswana are technically, allocatively and economically inefficient.

In addition to the above, it was hypothesized input subsidies have no effect on the economic efficiency of sorghum producers in Botswana. From the positive and statistically significant subsidy dummy in the Tobit model (Table 4.5), we reject the null hypothesis of no effect of input subsidies on the economic efficiency of sorghum producers in Botswana. This means that input subsidies have a significant and positive effect on economic efficiency of sorghum producers in Botswana.

# CHAPTER FIVE: SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

## 5.1 Summary

The proliferation of arable farming in Botswana is largely constrained by harsh weather and poor soils and biohazards. As a result, the production of staple food crops like sorghum is low. Accordingly, Botswana relies largely on food imports for its food security. In an effort to support local production and reduce dependence on imports, the Government of Botswana instituted Integrated Support Programme for Arable Agriculture (ISPAAD) to facilitate farmer access to farm inputs. However, despite the ISPAAD, crop yields still remain below their potential level. In particular, sorghum yields range between 0.16 ton/ha and 1.83 ton/ha against their potential of 2.5 ton/ha. This begs the question of how well the input subsidies have affected the economic efficiency of sorghum producers in Botswana. This study was designed to fill this gap in knowledge. The overall objective was to examine the effect of input subsidies on economic efficiency of sorghum producers in Botswana. The specific objectives were to estimate the economic efficiency of sorghum producers in Botswana and assess the effect of agricultural input subsidies on the economic efficiency of sorghum producers in Botswana.

The study used time series sorghum input and output data for the period 1998-2017. The data were adjusted for both inflation and non-stationarity. Stochastic production and cost frontiers were respectively used to estimate sorghum producers' technical and allocative efficiency. The economic efficiency was calculated as the product of technical and allocative efficiency. A Tobit model eventually used to evaluate the effect input subsidies on sorghum producers' economic efficiency.

The study found average technical, allocative and economic efficiencies of 0.94, 0.67 and 0.64 respectively, suggesting substantial inefficiencies among Botswana's sorghum producers over the study period. Accordingly, sorghum producers' technical inefficiency would need to be reduced by 6 percent while allocative inefficiency would need to be reduced by 33 percent. The study also found that on average producers can increase their economic efficiency by reduction in total production costs by 37 percent. Input subsidies had a positive and significant effect on sorghum producers' economic efficiency. The control variable; political stability, rainfall variability and trade openness had, respectively, a positive, negative and positive influence on sorghum producers' economic efficiency.

## 5.2 Conclusions

The study provides evidence of high technical, allocative and economic inefficiencies among sorghum producers in Botswana over the study period. Although the mean technical efficiency score of 0.94 was relatively high, it lies below the efficient frontier of one. This indicates that Botswana's sorghum producers were technically inefficient during the study period. The technical inefficiency could be attributed to overuse of labour, seed and tractors but could be reduced through more formal education of sorghum producers. The high allocative inefficiency of sorghum producers largely arose from low technology adoption over time as suggested by the positive time trend of total costs variable. In addition, trade openness and especially sorghum imports from South Africa, increased producers' allocative inefficiency. Rainfall variability accounted for substantial allocative inefficiency perhaps due to Botswana's aridity and desert-like conditions.

As a result of the low technical and allocative efficiency, sorghum producers' economic efficiency was also low at only 64 percent. This suggests that, on average, sorghum producers in Botswana need to save 36 percent on total production costs in order to attain the optimal economic efficiency. Rainfall variability and trade openness reduced producers' economic efficiency while political stability and input subsidies promoted it. Therefore, it was beneficial to provide input subsidies to sorghum producers in Botswana over the study period.

## 5.3 Recommendations

Based on the findings of this study, the Government of Botswana should develop an adult training programme to provide education to sorghum farmers. Such knowledge would enable them to increase their technical and allocative efficiency. In addition, the Government of Botswana should continue subsidizing sorghum producers as the study has shown that the use of input subsidies had a positive effect on sorghum producers' economic efficiency. Further, the Government of Botswana should put in place climate-smart strategies to help sorghum producers cope with the adverse effect of rainfall variability. This can be achieved by availing drought-tolerant sorghum varieties and use of modern irrigation technologies to reduce the high dependence on rain-fed agriculture. The Government of Botswana should continue to promote political stability as it is a necessary condition for the achievement of economic efficiency as shown in this study.

Finally, the government should minimize sorghum imports through more inward-looking (macro)economic policies that reduce trade openness in order to increase sorghum producers' economic efficiency. However, Botswana, being a member of Southern African development community (SADC), seems not to benefit from it as its export base is still low and at the infancy stage. Accordingly, the government should encourage efficient sorghum production to reduce imports.

### 5.4 Areas for further research

This study addressed the effect of input subsidies on the economic efficiency of sorghum producers in Botswana. There is therefore need for further research to assess the effect of input subsidies on economic efficiency of other cereals that compete for resources with sorghum. Such a study could also conduct a meta-frontier analysis on effect of input subsidies on different crops in different regions of Botswana to enable the proper targeting of input subsidies in those regions.

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## APPENDICES

**Appendix1: Test presence of technical inefficiency**

Table A1.1. Test for presence of technical inefficiency

| Hypothesis | Parameters | Likelihood ratio | Chi square | Decision |
|---|---|---|---|---|
| Presence of ineffiencies | H0: $\gamma = 0$ | 25.90 | 9.448 | Reject Ho |

Source: Authors' computation

**Appendix 2: Test for presence of allocative inefficiencies**

Table A21. Presence of allocative inefficiencies

| Hypothesis | Parameters | Likelihood ratio | Chi-square | Decision |
|---|---|---|---|---|
| Presence of inefficiencies | H0: $\gamma = 0$ | 20.35 | 7.81 | Reject Ho |

Source: Authors' computation

**Appendix 3: Stationary test at level and first differencing for input prices**

A3.1. Augmented Dickey Fuller Test at level for wage rate

| Test statistics | 1% level | 5% level | 10% level | P-value |
|---|---|---|---|---|
| -2.191 | -4.380 | -3.600 | -3.240 | 0.49 |

Mackinnon (1996) one sided P-value

A3.2. Augmented Dickey Fuller Test at first difference for wage rate

| Test statistics | 1% level | 5% level | 10% level | P-value |
|---|---|---|---|---|
| -5.496 | -4.380 | -3.600 | -3.240 | |

Mackinnon (1996) one sided P-value

A3.3. Augmented Dickey Fuller Test at level for seed price

| Test statistics | 1% level | 5% level | 10% level | P-value |
|---|---|---|---|---|
| -1.806 | -4.380 | -3.60 | -3.240 | 0.702 |

Mackinnon (1996) one sided P-value

A3.4. Augmented Dickey Fuller Test at second difference for seed price

| Test statistics | 1% level | 5% level | 10% level | p-value |
|---|---|---|---|---|
| -4.538 | -4.380 | -3.600 | -3.240 | 0.0013 |

Mackinnon (1996) one sided P-value

A3.5. Augmented Dickey Fuller Test at level for fertilizer price

| Test statistics | 1% level | 5% level | 10% level | P-value |
|---|---|---|---|---|
| -2.290 | -4.380 | -3.600 | -3.240 | 0.440 |

Mackinnon (1996) one sided P-value

A3.6. Augmented Dickey Fuller Test at first differencing for fertilizer price

| Test statistics | 1% level | 5% level | 10% level | p-value |
|---|---|---|---|---|
| -4.517 | -4.380 | -3.600 | -3.240 | 0.0014 |

Mackinnon (1996) one sided P-valueA3.7. Augmented Dickey Fuller Test at level for tractor price

| Test statistics | 1% level | 5% level | 10% level | P-value |
|---|---|---|---|---|
| -0.700 | -4.380 | -3.600 | -3.240 | 0.973 |

Mackinnon (1996) one sided P-value

A3.8. Augmented Dickey fuller test at first differencing for tractor price

| Test statistics | 1% level | 5% level | 10% level | p-value |
|---|---|---|---|---|
| -6.759 | -4.380 | -3.600 | -3.240 | 0.0000 |

Mackinnon (1996) one sided P-value

A3.9. Augmented Dickey Fuller Test at level for Total cost

| Test statistics | 1% critical statistics | 5% critical value | 10% critical value | P-value |
|---|---|---|---|---|
| -1.610 | -4.380 | -3.600 | -3.240 | 0.7886 |

Mackinnon (1996) one sided P-value

A3.10. Augmented Dickey Fuller Test at first difference level for Total cost

| Test statistics | 1% level | 5% level | 10% level | P-value |
|---|---|---|---|---|
| -5.68 | -4.380 | -3.600 | -3.240 | 0.0000 |

Mackinnon (1996) one sided P-value

**Appendix 4: Autocorrelation test for total cost function**

Appendix A4.1. OLS estimation and Durbin- Watson test for autocorrelation on total costs

| Dtotal cost | coefficient | Std. Error | T ratio | p-value | Confidence interval | |
|---|---|---|---|---|---|---|
| dtractor price | 0.0103287 | 0.0055851 | 1.85 | 0.087 | -0.001737 | 0.0223947 |
| dfertilizer price | 0.0087335 | 0.0079205 | 1.10 | 0.290 | -0.008377 | 0.0258446 |
| Dseedprice | -0.052906 | 0.0371387 | -1.42 | 0.178 | -0.133139 | -0.022394 |
| Dlnwage | 0.9884168 | 0.0434961 | 22.72 | 0.000 | 0.8944492 | 1.082384 |
| Constant | 0.0402324 | 0.009647 | 4.17 | 0.001 | 0.0193912 | 0.0610735 |
| $R^2$ | 0.9771 | | | | | |
| F(4,13) | 138.72 | | | | | |
| Durbin-Watson statistics | 1.1322 | | | | | |
| Prob>F | 0.0000 | | | | | |
| Root MSE | 0.04047 | | | | | |

**Appendix 5: Autocorrelation test for production function**

Appendix A5.1. OLS estimation and Durbin -Watson test for autocorrelation on production

| Lnoutput | coefficient | SE | T ratio | p-value | Confidence interval | |
|---|---|---|---|---|---|---|
| Land | 0.05207 | 0.2393 | 0.22 | 0.831 | -0.469 | 0.5736722 |
| fertilizer | 0.0200 | 0.08736 | 0.23 | 0.823 | -0.1703 | 0.2103665 |
| Seed | 0.21824 | 0.27333 | 0.80 | 0.440 | -0.37730 | 0.8137981 |
| Labour | 0.12780 | 0.62001 | 0.21 | 0.840 | -1.223 | 1.478707 |
| tractor | 0.00685 | 0.0646 | 0.11 | 0.917 | -0.133 | 0.147611 |
| Constant | 6.198976 | 5.707283 | 1.09 | 0.299 | -6.23612 | 18.63408 |
| R-squared | 0.1583 | | | | | |
| F(4,13) | 0.45 | | | | | |
| Durbin-Watson statistics | 1.3338 | | | | | |
| Prob>F | 0.8045 | | | | | |
| Root MSE | 0.4227 | | | | | |

**Appendix 6: Test for Multicollinearity**

A6.1. Test for multicollinearity in production variables

| | seed | Fertilizer | tractor | Labour | Area |
|---|---|---|---|---|---|
| seed | 1 | | | | |
| Fertilizer | -0.1865 | 1 | | | |
| tractor | 0.1051 | -0.1582 | 1 | | |
| labour | -0.1059 | 0.4752 | 0.2203 | 1 | |
| Area | -0.1957 | 0.3377 | -0.1328 | 0.3141 | 1 |

A6.2. Test for multicollinearity in total cost variables

| | Seed price | Tractor price | Fertilizer price | Wage rate |
|---|---|---|---|---|
| Seed price | 1 | | | |
| Tractor price | 0.1405 | 1 | | |
| Fertilizer price | -0.3013 | -0.1625 | 1 | |
| Wage rate | -0.2544 | 0.0072 | 0.1125 | 1 |

A6.3. Test for multicollinearity in Inefficiency model

| | log subsidy | Log trade | Log poli | Log edu | Log research | Log rain |
|---|---|---|---|---|---|---|
| Log subsidy | 1 | | | | | |
| Log trade | -0.1068 | 1 | | | | |
| Log poli | 0.2468 | -0.0154 | 1 | | | |
| Log edu | 0.7710 | -0.3030 | 0.4450 | 1 | | |
| Log research | -0.7810 | 0.1243 | -0.2276 | -0.5054 | 1 | |
| Log rain | -0.0759 | 0.0466 | -0.0254 | -0.1394 | -0.0824 | 1 |

A6.4. Test for multicollinearity in Translog cost

| | Wage*wage | Wage*seed | Trac*wage | wage | Seed*ferti | Tract*ferti | D2seed | Yield |
|---|---|---|---|---|---|---|---|---|
| Wage*wage | 1 | | | | | | | |
| Wage*seed | -0.909 | 1 | | | | | | |
| Trac*wage | 0.8520 | -0.761 | 1 | | | | | |
| Wage | -0.804 | 0.768 | -0.697 | 1 | | | | |
| Seed*ferti | 0.165 | -0.271 | 0.114 | -0.388 | 1 | | | |
| Trac*ferti | -0.166 | 0.045 | -0.462 | 0.308 | -0.115 | 1 | | |
| D2seed | 0.337 | -0.1939 | 0.251 | -0.254 | -0.238 | -0.1935 | 1 | |
| Yield | -0.382 | 0.425 | -0.490 | 0.334 | -0.01 | 0.057 | -0.114 | 1 |

Appendix 6.5. Test for multicollinearity in Translog production function

| | seed | fert | trac | labor | Seed*fert | Fert*fert | Trac*trac | Lab*seed | Trac*labor |
|---|---|---|---|---|---|---|---|---|---|
| Seed | 1 | | | | | | | | |
| Fert | -0.186 | 1 | | | | | | | |
| Trac | 0.105 | -0.158 | 1 | | | | | | |
| Labor | -0.105 | 0.475 | 0.220 | 1 | | | | | |
| Seed*fert | 0.379 | 0.837 | -0.082 | 0.393 | 1 | | | | |
| Fert*fert | -0.188 | 0.994 | -0.130 | 0.477 | 0.831 | 1 | | | |
| Trac*trac | 0.075 | -0.173 | 0.993 | 0.194 | -0.114 | -0.147 | 1 | | |
| Labo*seed | 0.657 | -0.212 | 0.258 | 0.679 | 0.575 | 0.2205 | 0.215 | 1 | |
| Trac*labo | 0.085 | 0.023 | 0.945 | 0.518 | 0.077 | 0.046 | 0.932 | 0.4672 | 1 |

**Appendix7: Test for heteroscedasticity**

A7.1. test for heteroscedasticity in cost function

| **parameter** | **Coefficient** | **SE** | **t** |
|---|---|---|---|
| D2seed | 1.126 | 0.535 | 2.110 |
| Dfertilizer | -0.006 | 0.112 | -0.060 |
| Dtractor | -0.092 | 0.081 | -1.130 |
| dlnwage | 0.754 | 0.416 | 1.810 |
| constant | 0.475 | 0.138 | 3.440 |
| F(4,15) | 1.78 | | |
| Prob>F | 0.1856 | | |
| R-squared | 0.3218 | | |
| Adj R-squared | 0.1409 | | |
| Root MSE | 0.611122 | | |

Appendix A7.2. Test for heteroscedasticity in production function

| **parameter** | **Coefficient** | **SE** | **t** |
|---|---|---|---|
| Ln seed | 0.0004 | 0.0005 | 0.500 |
| Ln fertilizer | 0.0001 | 0.0003 | 0.550 |
| Ln tractor | 0.0001 | 0.0002 | 0.780 |
| Ln labour | 0.0002 | 0.0004 | 0.560 |
| Ln area | -0.0002 | 0.0006 | -0.270 |
| constant | -0.047 | 0.0076 | -0.820 |
| F(4,15) | 0.44 | | |
| Prob>F | 0.7347 | | |
| R-squared | 0.1647 | | |
| Adj R-squared | -0.1337 | | |
| Root MSE | 0.00125 | | |