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Analysis of Factors Influencing the Technical Efficiency of Smallholder Maize Farmers in Northern Province, Zambia

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I dedicate this work to my grandmother, Theresa Mulenga, my late father, Joseph Silomba, and my three wonderful mothers: Grace Mwamba, Flaviour Mwamba and Maureen Mwamba.

Thank you for not crippling my wings!

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Abstract

This study investigated the efficiency of smallholder farmers in Northern Province, Zambia. The research utilized data collected in 2014/2015, which was representative of the province and gathered by the Institute for Agricultural Policy Research Institute in collaboration with the Zambia Statistical Agency and Ministry of Agriculture. To assess technical efficiency, a stochastic production function with a translog functional form was developed. The model included four characteristics related to the farms and farmers, as well as three institutional variables, all of which were found to be statistically significant. The efficiency levels observed ranged from 0.02 to 0.93, with a median value of 0.67. The findings indicated that the primary factors influencing total output were the extent of cultivated land, followed by the use of fertilizers. The empirical analysis demonstrated that access to credit, extension services, and farmer input support programs, as well as the distance between the household's residence and the farm, the gender, age, and educational level of the household head, all played vital roles in determining the technical efficiency at the farm level.

Keywords: Smallholders**,** Technical efficiency, Stochastic Frontier Analysis (SFA), credit, farmer input support programme, Northern Province, Zambia.

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Chapter 1: Introduction

1.1 Background to the Zambian Economy

During the period spanning from 1940 to 1970, the price of copper experienced a consistent increase, which positioned Zambia as one of the most successful nations in sub-Saharan Africa upon gaining independence from Britain in 1964 (Seshamani, 1992). The stability and favourable nature of exchange and inflation rates, coupled with low interest rates, contributed to this prosperity. Furthermore, the elevated copper price resulted in a positive trade balance for the country (Karmiloff, 1990).

Regrettably, this era of affluence was short-lived, as copper prices plummeted in the mid-1970s. Consequently, Zambia's terms-of-trade index suffered a staggering decline of 49% within a single year. Subsequently, from 1975 onwards, the country experienced the worst terms of trade among sub-Saharan African nations (Wulf, 1988). The value of commodity exports dwindled by over forty percent, thereby destabilizing the overall economy (Karmiloff, 1990). Throughout the period from 1974 to 1985, economic growth slowed down to less than 1% per annum, while the population continued to grow at a rate of 3.3% per annum (Saasa, 1994).

In an endeavour to counter the economic downturn, the government resorted to accumulating more debt, which eventually plunged Zambia into a severe debt crisis (Wulf, 1988). Subsequently, measures were undertaken to restructure and diversify the economy, shifting the emphasis away from copper and towards agriculture. A key focus was placed on enhancing the productivity of smallholder agriculture to ensure food security and alleviate rural poverty (Kydd, 1988). It was believed that by promoting the adoption of appropriate modern agricultural technologies among smallholder farmers, positive effects would be observed in the sector's productivity (Thurlow and Wobst, 2006). The government implemented a series of strategies and reforms to improve the performance of the agricultural sector. These included setting prices for most crops, providing subsidies to farmers in remote areas through direct payments to marketing agencies, and offering cross-subsidies to farmers located in urban and peri-urban areas (Kydd, 1988 and Seshamani, 1992). These efforts were aimed at enhancing the overall performance of the agriculture sector.

Between 1980 and 1994, Zambia’s economy was in turmoil. See Figure 1. In the early 1980s 30-40% of the economy derived from services. The primary sectors of agriculture and mining each contributed about 25% while manufacturing added about 15%. Between 1985 and 1995 the copper price collapsed, which reduced the mining sector’s contribution to less than 15%. Weakness in copper spilled over into the services sector whose contribution fell to 25%, barely half of the sector’s earlier share. With the copper economy shrinking the rest of the economy became more prominent. Copper prices recovered in 1993 and there was an immediate associated changes in the service sector's contribution to the overall economy, and together it had an adverse effect on agriculture and non-copper manufacturing. Over the following two decades the contribution of the manufacturing sector hovered around 10% of gross domestic product (GDP) while agriculture returned to levels last observed in the 1980s and the service sector continued to grow.

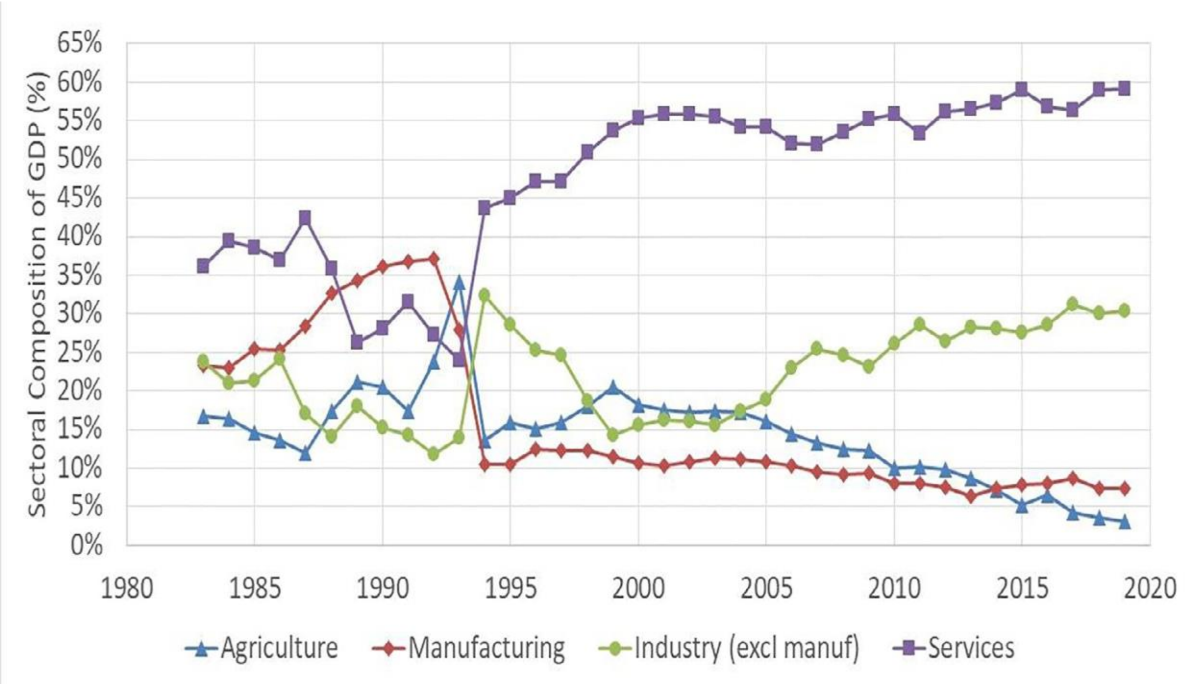

Figure 1: Zambia Sectoral Shares, 1980-2020 (Source: Zambia Ministry of Finance, 2021)

The mining sector experienced another slump during the early 2000s but grow steadily over the period 2005 to 2017 and continues to be a major driver of the economy, accounting for 17.5 percent of GDP and over 70 percent of foreign exchange earnings in 2021. Production has, however, stagnated at an annual average of 797,000 metric tonnes in the last 5 years (Zambia Ministry of Finance, 2022).

1.2 A brief history of agricultural policies in Zambia

In 1991, Zambia witnessed a significant political shift as the United National Independence Party (UNIP) government, led by Kenneth Kaunda, was defeated in elections by Fredrick Chiluba's Movement for Multiparty Democracy (MMD). The new administration embarked on an ambitious policy agenda aimed at liberalizing the economy, which involved the elimination of input and output subsidies, exchange controls, and import/export embargoes (Howard and Mungoma, 1996). However, the country faced a severe drought in 1991/2, resulting in the destruction of the maize crop and a substantial increase in consumer prices that became unsustainable. To address this crisis, the MMD government took action by establishing the Food Reserve Agency to enforce price ceilings and implement a surplus removal scheme (Neubert, et al., 2011).

In 2001, under the leadership of Levy Patrick Mwanawasa, the New Deal MMD government implemented various maize subsidy programs with the aim of boosting maize production (Neubert, et al., 2011). One such program was the Food Security Pack, which targeted vulnerable rural households engaged in farming on less than one hectare of land, providing them with support (Neubert, et al., 2011). To expand the program's impact, the government initiated the distribution of subsidized fertilizers on a large scale to smallholder farmers registered through cooperatives, transitioning the fertilizer support program into a grant-based system (Zambia Ministry of Agriculture and Cooperatives, 2008; Chapoto and Jayne, 2006). The primary objective of this program was to encourage private entities to participate in the supply of fertilizers and hybrid seeds, while also ensuring timely access to agricultural inputs for smallholder farmers (Mason, et al., 2013).

Significantly, the aforementioned government actions and reforms, namely the implementation of a price ceiling and a surplus removal scheme by the Food Reserve Agency, along with the introduction of production subsidies, exhibit a certain level of contradiction with the objective of augmenting maize production. The reintroduction of production subsidy programs, while in effect, proved to be less effective due to the continued enforcement of price ceilings. Consequently, the most efficient governmental policy would have entailed either entirely abolishing or, at the very least, raising the price ceiling, thereby rendering maize production a profitable venture. Such a course of action would also serve to stimulate both production and supply.

In 2008, the Fertiliser Support Programme was changed to Farmer Input Support Programme. With this change, the government distributed smaller amounts of fertiliser to more beneficiaries identified not only by means testing but also nominated by local community leaders, women cooperatives, and youth farmer organisations (Mason, et al., 2013). More crops such as rice, sorghum and groundnuts were further added to the programme, whereas in the past, only maize was considered (Zambia Ministry of Agriculture and Cooperatives, 2008). The third innovation under Farmer Input Support Programme involved the land under cultivation. To qualify for the programme, a farmer was now supposed to cultivate half a hectare of land in line with the reduction in the size of input (Mason, et al., 2013). However, like previous versions of input support programmes, the Farmer Input Support Programme was characterised by several changes. Key among them included high cost of delivering inputs to various districts, limited private sector participation in the delivery of inputs, limited crops grown by farmers and resource allocative inefficiency (unintended beneficiaries received inputs, and in certain cases, beneficiaries were duplicated) (Mason, et al., 2018).

To offset these challenges, in 2015, the government introduced Farmer Input Support Programme e-voucher (e-FISP) as a replacement for the conventional Farmer Input Support Programme that used paper vouchers. Initially, the government used a combination of direct input support and e-voucher system, and only fully-implement the e-Voucher system during the 2017/2018 farming season. The inputs were delivered through a combination of the Direct Input Support and electronic Voucher system (e-voucher) (Mason, et al., 2018). The e-Vouchers administration of Farmer Input Support was thought to be less costly to administer and strengthened the distribution chains (Mason, et al., 2018).

Over time, the government's expenditure on farmer input support programme increased significantly in nominal terms without a corresponding increase in the number of beneficiaries and input package allocations (Zambia Ministry of Finance, 2021). In 2019, the Farmer Input Support Programme budgetary allocation accounted for the largest percentage of total government spending on agriculture (World Bank, 2021). In 2020 the total expenditure increased by more than half the budget for the entire agricultural sector (World Bank, 2021). Despite this increase, some smallholder beneficiaries reported having received fewer inputs compared to others (Zambia Ministry of Finance, 2021, Zambia Ministry of Finance, 2022). What is more, in certain cases where the e-voucher system was employed, some smallholder farmers indicated not receiving inputs even though they made contributions. Equity in terms of allocation and distribution of inputs. Some regions received more inputs in comparison to others (Zambia Ministry of Finance, 2021, Zambia Ministry of Finance, 2022).

With the transition of government in 2021, the United Party for National Development (UPND), under the leadership of Hakainde Hichilema, embarked on a new era known as the New Dawn. This administration made ambitious promises to effectively tackle the aforementioned challenges, particularly by implementing a comprehensive agriculture support program that encompasses extension services. The program, slated to commence in the upcoming farming season of 2022/23 starting in October, has been allocated funding in Zambia's national budgets for 2022 and 2023 (Zambia Ministry of Finance, 2021). Its primary objective is to facilitate the supply of high-quality agricultural inputs in a cost-effective manner. Notably, the revised program will also encompass the provision of extension services, access to production credit, irrigation facilities, support for value addition, and improvements in storage and logistics. To ensure that subsidized seeds and fertilizers are solely provided to the intended and deserving farmers, the government has emphasized its commitment to scrutinizing the beneficiaries meticulously (Zambia Ministry of Finance, 2022, p. 14).

The New Dawn government has already taken tangible steps to demonstrate its dedication to supporting the agriculture sector. In July 2022, the president announced his directive to the Minister of Finance to increase funding for fertilizer assistance through supplementary budget allocations, a move subsequently approved by parliament.

The New Dawn government has expressed its belief that the implementation of a comprehensive agriculture support programme will result in more effective targeting, promote crop diversification, ensure equitable distribution of benefits among all recipients, and ultimately lead to increased production and productivity within the agricultural sector in Zambia (Zambia Ministry of Finance, 2021). Additionally, the government aims to prioritize food security, particularly among vulnerable populations (Zambia Ministry of Finance, 2022). However, the effectiveness and inclusivity of the New Dawn government's agricultural policy, as well as its ability to achieve food security and significantly reduce poverty in Zambia, remain uncertain. To accomplish these goals, it is imperative to enhance the productivity of the agriculture sector and improve the efficiency of smallholder farmers.

1.3 Problem Context

In spite of numerous endeavours to enhance agricultural production in Zambia, rural households in the country continue to grapple with poverty. According to the United Nations' Office for the Coordination of Humanitarian Affairs (2021), more than 1.5 million Zambians are extremely food insecure. The agricultural sector faces a multitude of challenges that impede its progress, encompassing limited access to production credit, insufficient integration into commercial value chains, inadequate provision of inputs, and a lack of access to agricultural technical services (Thurlow and Wobst, 2013; World Bank, 2021; Zambia Ministry of Finance, 2021). It is noteworthy that Zambia's Eighth National Development Plan underscores the stagnant growth of the agricultural sector, which experienced an increase of less than half a percent between 2011 and 2020 (Zambia Ministry of Finance, 2022). Moreover, during this period, the sector contributed only 5.8 percent to the total gross domestic product (Zambia Ministry of Finance, 2022). Despite agriculture being the primary source of livelihood for over seventy percent of the population, its growth rate has been lower than the population growth rate, standing at 2.8 percent annually (Zambia Ministry of Finance, 2022).

Consequently, the income levels and living standards of rural households reliant on agriculture have significantly declined (Zambia Ministry of Finance, 2021). The underperformance of smallholder farmers, characterized by low productivity and technical inefficiency, has been identified as a key factor contributing to the sluggish growth in the agricultural sector (Mason et al., 2018). Therefore, an analysis of the factors influencing the technical efficiency of smallholder farmers, particularly in predominantly agricultural regions like Northern Province, is imperative.

1.4 Objectives and Research Questions

Against this background, the thrust of this study is to investigate the technical efficiency of smallholder maize farmers in the Northern Province of Zambia, and to discover their inefficiency factors. Specifically, the study will attempt to answer the following empirical questions:

1. What is the status and extent of access to production credit among smallholder maize farmers in Northern Province, Zambia and how does credit affect both male-headed household's and female-headed level of technical efficiency?
2. Does access to extension services help improve the technical efficiency of smallholders, and what sort of services are available for maize producers in Northern Province?
3. What is the coverage of farmer input support programme in Northern Province, and how does the programme affect smallholders' technical efficiency?
4. What are the implications of farm and farmers characteristics such as distance between homestead and farm, age of farm household head, gender of farm household head and level of education of farm household head?

1.5 Research Hypothesis

The null hypothesis outlined below will be tested:

H_0Smallholder maize farmers in Northern Province are on average not technically efficient.

H_0: Institutional factors such as access to credit, access to extension services and access to farmer input support programme do significantly influence farmers technical efficiency.

H_0: farm and farmer characteristics such as distance between homestead and farm, gender of household head, age of household head and level of education of household head significantly influence farmers technical efficiency.

1.6 Organisation of the Study

The rest of the dissertation proceeds as follows: The literature on model specification and factors that influence productivity is reviewed in chapter 2. Chapter 3, on data and methods outlines the research strategy, introduces the dataset, and presents the preliminary specification tests. The main results are presented in Chapter 4, discussion of main results in chapter 5, and the policy significance of the study follows in chapter 6. Appendix 1 contains excerpts from the questionnaire on the variables used in model specification, appendix 2 contains the data used.

Chapter 2: Literature Review

The commencement of this chapter is marked by a comprehensive exposition on efficiency measurement, delving into its theoretical underpinnings and the conceptual framework employed in this particular investigation. A panoramic survey of various empirical studies conducted in Sub-Saharan Africa is subsequently presented, which subsequently transitions to a focused examination of the Zambian landscape. Ultimately, this chapter culminates with a succinct summary highlighting the study's valuable contributions to the extant body of literature.

2.1 The concept of technical efficiency and measurement

The concept of efficiency has become commonplace in most agricultural studies. The idea is to find out how the decision-making agents (typically firms) transform the inputs into outputs. Broadly, two methods that have been developed to measure production efficiency parametric Stochastic Frontier Models which was developed independently by Aigner, et al. (1977) and Meeusen and Van den Broeck (1977) and the non-parametric Data Envelopment Analysis (DEA), which was initially used by Charnes, at al. (1978). As Wadud and White (2000) note, determining which of the methods to use is normally a determined by the availability of data and the objective of the research. Under a non-parametric method, decision-making agents (firms) are considered to have absolute control over the factors of production (inputs) and the deviation or departure from the frontier are attributed to technical inefficiency (Battese and Coelli, 1995; Kumbhakar, et al., 2000).

Data Envelopment Analysis is silent on functional form, and thereby it allows the researcher without any priori ideas about functional form to mix observations representing different technologies (Aigner, et al., 1977). While this is often offered as an advantage in the literature, the present study considers it to be a disadvantage since it could produce misleading results.

When farmers operate under uncertainty part of the observed inefficiency deviations from the frontier is due to inadequate management skills and part of it is due to randomness, including randomness in management. The main advantage of the stochastic frontier method is that it replaces observed input-output ratios with estimated ratios. The error term is decomposed into white noise (measurement error or unobserved stochastic variation in the environment) and observed differences in a farmer's circumstances or skill (e.g. education or rainfall received) and the latter is called technical inefficiency (Hayatullah, 2017; Aigner, et al. 1977; Meeusen and Van den Broeck, 1977).The exogeneous shocks that are not controlled by the production function, which comprises errors emanating from measurement discrepancies and statistical noise which are common in empirical relations (Aigner, et al. 1977; Kumbhakar and Lovell, 2000).

Wadud and White (2000) points out that the stochastic frontier approach (SFA) is advantageous because it allows for construction of intervals and hypothesis testing somethings is not possible to do using the non-parametric approach. The advantages notwithstanding, the SFA approach also has disadvantages, one of them being that a functional form for the frontier technology must be determined or assumed. The second reason relates to the distribution of technical inefficiency term which also requires a prior assumption of its functional form (Hayatullah, 2017).

As in Battese and Coelli (1995), the present study employs a parametric approach (stochastic frontier analysis) instead of the Data Envelopment Analysis approach. This is because smallholder rural agriculture in most cases exhibits random shocks (farmers tend to be affected by external characteristics outside their control such as climatic conditions and inefficiency effects) and because the overriding goal of the study is to measure the contribution of three conditional variables on measured efficiency. This is not possible in the Data Envelopment Analysis approach.

Technical efficiency has become the standard method for measuring the performance of commercial farmers and smallholder and subsistence producers alike (Bravo-Ureta, at al., 2007; Musaba and Bwacha, 2014; Mango, et al., 2015; Prasanna and Lakmali, 2016; Rana and Bapari, 2018). According to Farrell (1957), an agent (farmer) achieves economic efficiency when the costs associated with production are significantly low, and consumer(s) are willing to purchase a mixture of goods (products, farm produce, etc.) and services . Farrell (1957) further divides economic efficiency measure into two key components: allocative and technical efficiency.

The first measure is allocative efficiency (also called the input-oriented efficiency), which denotes the ability of a farmer to utilise a mixture of agricultural inputs to produce a given level of output at the prevailing prices and technology. The second efficiency measure is known as technical efficiency (also called output-oriented efficiency). Technical efficiency entails that economic agents (farmers) produce the highest possible level output given available set of production inputs. This means that technical efficient economic agents do not waste available resources (Farrell, 1957).

According to Farrell (1957), technical efficiency is only achieved if an agent (farmer) can produce as much as possible (of any product) by leveraging on the available input combination. Assuming constant returns to scale, Farrell (1957) showed technical efficiency using two inputs, $X_1\ and\ X_2$, to produce a single output, Y. This was depicted by Coelli, et al. (2005) and illustrated in Figure 2 below (input-oriented efficiency). Line SS' represents the fully efficient economic agent (farmer), which makes it possible for technical efficiency to be measured.

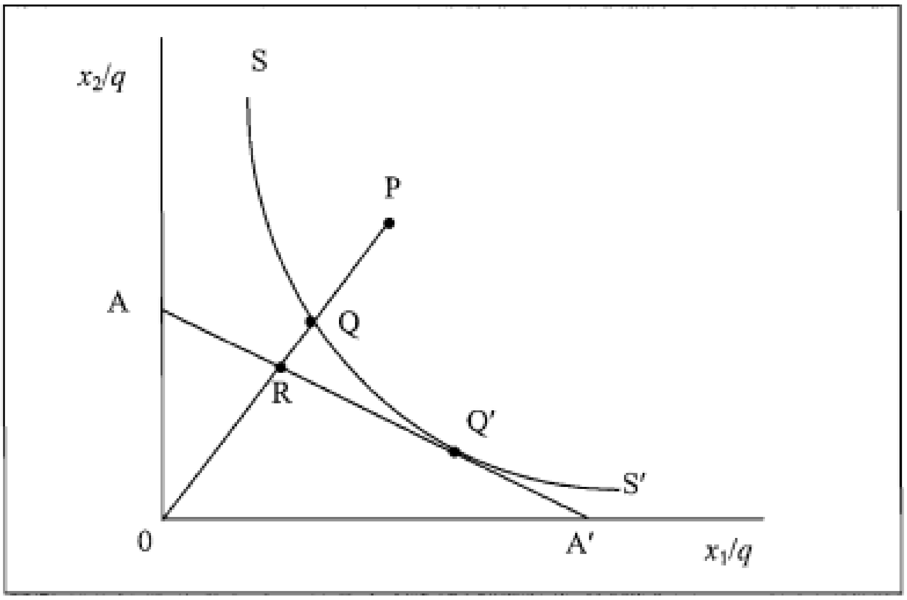

Figure 2: Technical and Allocative Efficiencies (Source: Coelli at al., 2005)

Point P in figure 2 above denotes an inefficient farmer. Assuming a farmer is utilising a set of inputs (represented by point P) to produce a unit of output, then the distance QP depicts the farmer's technical inefficiency. *Technical inefficiency* (QP) in this case entails that output will remain unchanged when the inputs (x_1 and x_2) are reduced proportionally. To achieve an efficient production, the inputs (x_1 and x_2) must be reduced by the ratio $\frac{QP}{OP}$ (see figure 2). *Technical efficiency* (TE) of a farmer is therefore given by TE= $\frac{OQ}{OP}$= [1- $\frac{QP}{OP}$]. Technical efficiency scores range from zero to one. When the technical efficiency score is equal to one, then a farmer is said to be fully technically efficient (as depicted by point Q which is on the efficient frontier). Similarly, when the technical efficiency score is equal to zero, a farmer is said to be fully technically inefficient. On the other hand, Coelli, et al. (2005) noted that if the gradient of the isocost line (denoted by AA') represented the price ratio for the inputs, then the ratio $\frac{OR}{OQ}$ could represent *allocative efficiency* (AE). The focus of this study, however, is technical of efficiency of smallholder farmers in Northern Province, Zambia.

2.2 Cobb-Douglas Production Versus Translog functional forms

When implementing stochastic frontier analysis, it is important to specify the production technology and inefficiency variables correctly. Under the stochastic frontier analysis with inefficiency effects (Battese and Coelli, 1995), the distribution of the inefficiency term can the gamma, exponential, truncated normal or half normal (Jondrow, et al., 1982, Duffy and Papageorgiou, 2000; Kneller and Stevens, 2003). Three commonly used functional forms in empirical studies are Cobb-Douglas, the constant elasticity of substitution and the translogariththmic functions (Constantin, at al., 2009).

Among the three specifications, the most widely used function is the translog specification due to the fact that it provides a good first-order approximation to a variety of functions including the constant elasticity of substitution and in special cases the Cobb-Douglas (Kneller and Steven, 2003; Constantin, et al., 2009), The Cobb-Douglas production function is easier to measure and interpret since the coefficients are the elasticities (Duffy and Papageorgiou, 2000; Constantin, et al., 2009). The multiplicative Cobb-Douglas production function can be estimated with the ordinary least squares if the variables are transformed into natural logarithms (Constantin, et al., 2009). One key disadvantage of the Cobb-Douglas production function is that it assumes constant elasticity of substitution between the associated factors of production (Constantin, et al., 2009). This assumption also means that the inputs display a constant cost share (Miller, 2008; Constantin, et al., 2009).

Addressing this disadvantage of using the Cobb-Douglas model, a translog function form is preferred. The use of the translog model is because of the fact that it does not require the constant elasticity of substitution assumption (which is a must when using the Cobb-Douglas function). Notably also, the Cobb-Douglas function is a special case of the translog if there is constant elasticity of substitution (Kumbhakar and Tsionas, 2006). Several studies have compared the Cobb-Douglas production function and the translog production function. Like Constantin, et al. (2009) most empirical applications now routinely test if the coefficients on the square and the interaction terms are significantly different from zero by applying likelihood ratio tests. If the null hypothesis is rejected, then translog production function is superior to the Cobb-Douglas.

Using panel data for eighty-two countries for a period of twenty years, Duffy and Papageorgiou (2000) also rejected the null-hypothesis and adopted the translog as the best function to measure technical efficiency. Piesse et al. (2018) reached the same conclusion for a panel dataset of 77 wine farms studied over a decade and translog even proved superior to Cobb Douglas for fitting a SFA model on an unbalanced panel of just 199 observations in a case study of livestock production in arid areas (Conradie et al, 2019)When sample size falls much below that, for example to n = 125 in the case of Conradie et al. (2021) or to n = 94 in Conradie and Genis (2020), the LR test fail to reject the assumption that the coefficients on the interaction and squared term are jointly zero, and the analysis proceeds with a Cobb Douglas functional form.

Other empirical studies have also found the translog to more useful and informative compared to the Cobb-Douglas and the data envelopment analysis (DEA). For example, Headey et al. (2010) compared the results of the DEA to that of the translog and found that the translog fitted the data better than the DEA. Other advantages associated with the translog frontier analysis are that the results obtained from the translog are more useful in providing additional information with regards to how the variables are interacting and the SFA approach is more flexible with regards to the assumption of the shape of the factor shares (Kumbhakar and Lovell, 2000; Kneller and Stevens, 2003).

2.3 Empirical Literature: Technical Efficiency of Smallholder Farmers

In any form of production, whether in area of agriculture or manufacturing sector, financial resources play a very important role in the production process. With increased access to credit, smallholder agricultural households can potentially meet their various financial needs, including the purchase of improved inputs such as seeds, fertiliser, agrochemicals and hiring of additional labour. Abate et al. (2016) and Mariyono (2019) observe that access to financial resources help smallholder farmers to start using modern farming technologies that has the potential to increase their productivity. Further, smallholder farmer who have access to financial resources become increasingly more resilient to external shocks such as changes in climate conditions (Janzen and Carter, 2019).

The literature abounds with technical efficiency studies showing that access to financial resources for smallholder farmers plays an important role in improving farm efficiency. Studies differ in terms of methods and context. Koricho and Ahmed (2021) examined the impact of access to credit on the technical efficiency of maize production by Ethiopian smallholders using a combination of a Propensity Score Matching technique with a stochastic frontier model. Their results showed that credit improved smallholder farmers technical efficiency. The main advantage of combining the propensity score matching and stochastic frontier approach is that it eliminates the effects of self-selection into the treatment group, which would otherwise be attributed to one or more inefficiency effects. However, the present study does not adopt this method because only a small number of the sample reported having access to credit. Therefore, only the stochastic frontier approach was adopted.

Matsvai, et al. (2020) examined the impact of access to microfinance on the productivity and technical efficiency of smallholder sugarcane farmers in Zimbabwe using household level survey cross-sectional data. The study used Translog Stochastic Frontier Analysis. The translog production function revealed that access to credit, extension services, tertiary education, secondary education, farming experience of the household head and farming experience positively improved technical efficiency. The translog stochastic frontier has a comparative advantage over the Cobb-Douglas approach since it enables researchers to determine the interaction between inputs in the production function. This approach is further important because it reveals whether the regressors have a linear or nonlinear relationship with the dependant variable, output. Like to Matsvai, et al. (2020), the present study adopts the translog stochastic frontier analysis approach. This is because the sample is large enough, which is one of the requirements for fitting the many parameters in a translog functional form.

Dube and Guveya (2014) employed the Data Envelopment Analysis (DEA) approach to investigate the technical efficiency of smallholder tea farmers in an out-grower scheme in Zimbabwe. The authors used cross-section data collected from a sample of 50 smallholder farmers. Technical efficiencies of farmers ranged from 0.37 to 1.0, with the mean being 0.79. Tea farming experience, the amount of labour used in the production process, the area under cultivation, access to agricultural technical services, and yield positively and significantly improved technical efficiency. Amount of fertiliser in production, age and extent of commercialisation had negatively and significantly influenced technical efficiency. However, the age of tea was found to be statistically insignificant. While the DEA approach allows for simultaneous analysis of outputs and inputs, it ignores the effect of exogeneous variables and statistical errors. The DEA approach also presents difficulties when it comes to performing statistical tests with the results. For these reasons, the present study uses Stochastic Frontier Analysis approach which overcomes these shortcomings and is more flexible with regards to the assumption of the shape of the factor shares (Kumbhakar and Lovell, 2000; Kneller and Stevens, 2003).

Dessale (2019) used a combination of both primary and secondary data as well as quantitative and qualitative cross-sectional household data to analyse the technical efficiency of smallholder wheat growing farmers in Ethiopia. The authors used a Cobb-Douglas Stochastic Frontier Model. Results showed that wheat output was positively and significantly influenced by land size, labour, number of oxen and fertiliser. The estimated mean levels of efficiency were 82%. Age of household head, education of household head, use of improved seed, access to credit and training were found to improve the technical efficiency of farmers. Although the Cobb-Douglas production function is straight forward and easier to use, it does not allow the researcher to see how the regressors are interaction. The Cobb-Douglass is also convenient especially when the sample size is small. Therefore, in the present study, the Translog Stochastic Frontier Approach is adopted. Key advantages associated with the translog frontier analysis are that the results obtained from the translog are more useful in providing additional information with regards to how the variables are interacting.

Mango, et al. (2015) used a linearised Cobb-Douglas production function to analyse the technical efficiency of smallholder maize farmers in Zimbabwe. The authors used randomly selected sample of

522 maize producers. Results indicated that approximately 90% farmers in the sample were between 60 and 75% technically efficient. The mean efficiency score was 65%. Agricultural extension services and household size negatively and significantly influenced technical efficiency. Gender of household head, frequency of extension visits, farming region and farm size positively and significantly improved technical efficiency. Access to credit, weeding frequency, cattle ownership, age of household head, farming experience, level of education of household head and adoption of conservation agriculture practices were found to be statistically insignificant. Contrary to the author's findings, this study expected access to credit and access to extension services to improve the efficiency of smallholder farmers. This is because availability and accessibility of credit would allow for timely access to sufficient inputs. The present study expects farmers technical knowledge to adopt efficient farming practices. In terms of model, one key disadvantage of the Cobb-Douglas production function is that it assumes constant elasticity of substitution between the associated factors of production (Constantin, et al., 2009). This assumption also means that the inputs display a constant cost share (Miller, 2008; Constantin, et al., 2009). Addressing this shortcoming of the Cobb-Douglas functional form, the present study uses the translog stochastic production function, which relaxes the assumption of constant elasticity of substitution is preferred. The Cobb-Douglas function is a special case of the translog if there is constant elasticity of substitution (Kumbhakar and Tsionas, 2006).

Dube, et al. (2017) assessed the technical efficiency of smallholder tobacco farmers in Makoni district of Zimbabwe using a Cobb-Douglas stochastic frontier analysis (SFA) approach. The authors used cross-sectional data from 98 randomly selected farmers constituting 78% contract farmers and 22% non-contract participating farmers. The study followed two-step estimation model. The authors started by specifying and estimating the Cobb-Douglas stochastic frontier production function and the prediction of technical efficiency effects. The authors then specified a regression model for the predicted technical inefficiency effect. Efficiency results showed that farmer type (contracted versus non-contracted), farmers level of education (at least secondary education), total cropping area and gender significantly improved technical efficiency. Conversely, access to loans apart from the contract farming credit negatively and significantly worsened technical efficiency of farmers. The authors found that male farmers were less efficient compared to their female counterparts and the results were significant at 1% level. The argument was that female farmers can just be as efficient as male farmers provided that individual characteristics and input levels are controlled. The negative effect of access to loans was based on the possibility that farmers with alternative loan sources could easily borrow to repay the contract farming loan. Therefore, this could lead to not using the contract farming loan optimally. The present study differs from this study because it considers farmers who do not have an already existing loan contract. It is therefore expected that access to credit should positively and significantly improve the technical efficiency of farmers in Northern Province. In terms of functional form, the Cobb-Douglass stochastic production function used in this study does not allow for the interaction of independent variables. Therefore, in the present study the translog stochastic production function is adopted.

Tchale and Sauer (2007) applied a stochastic error component approach to assess the technical efficiency of maize producers in Malawi using the flexible functional form of a translog production function. The authors used farm household and plot level cross-sectional data of 376 households (573 farm plots). The results provided evidence that credit provision, gender of household head, access to agricultural technical services, access to agricultural input and output markets positively, amount of rainfall and significantly influenced smallholders' technical efficiency. The authors attributed the significance of access to credit to the low level of access to production credit among smallholder farmers. This was further attributed to high interest rates and collateral requirements associated with the seasonal agricultural loans in Malawi. Similarly, it will be interesting to see the effect of access to credit on smallholder farmers' technical efficiency in Zambia where the lending rates are significantly high. The author's findings highlighted the importance of strengthening public policy bordering on provision of financial services for the smallholder to ensure poverty reduction.

Koirala, et al. (2015) used a Cobb-Douglas stochastic frontier production function to assess whether gender affected productivity and technical efficiency of rural smallholder farmers in Malawi. The authors used cross-sectional data collected through the integrated household survey in Malawi. Results showed that female farmers were more technically efficient than male farmers. This was contrary to priori expectations. The authors attributed female-headed households high efficiency scores to the use of more capital in agriculture production. The study also found that subsidies, access to credit, marital status, and level of education of farm operators positively and significantly improved technical efficiency. Months of informal labour, food security and age of farm operators had a negative and significant relationship with technical efficiency. Contrary to the findings of Koirala, et al. (2015), the present study expected male-headed farm households to be more technically efficient than female-headed households. This is because women face difficulties in having access to production credit (Fletschner, 2008). Women are also discriminated against access to agricultural technical services compared to their male counterparts (Udry, 1994).

Okoye et al. (2016) used a Cobb-Douglas stochastic frontier production function with inefficiency effects to measure the technical efficiency of smallholder cassava farmers in Madagascar. The authors used cross-sectional data of 180 smallholder rural farmers across 6 districts. Results showed that gender of household head, occupational status and age of household head negatively and significantly worsened technical efficiency. In terms of age, the authors submitted that older farmers are less energetic than younger ones, resulting in reduced productivity and technical efficiency levels. The level of education of the household head negatively and significantly worsened technical efficiency. This was contrary to the author's priori expectation. However, the authors argued that maybe more educated farmers in their sample tended to work part-time on their farms and had other livelihood options. Similar to level of education, household size negatively and significantly worsened the technical efficiency levels of farmers. This too was contrary to the priori expectation of the authors. The justification was that with large households, more resources would be channelled away from farm activities towards looking after family members. Farm size, membership of farmer organisation and farming experience were statistically insignificant.

Achandi (2018) employed the translog stochastic frontier model to analyse the determinants of technical efficiency of smallholder rice producers in Tanzania. The results showed that access to production credit, gender of household head, group membership, primary occupation of household head and fertiliser use increased smallholders' productivity and technical efficiency of production. Age of household head, growing in irrigated ecology, access to extension services and marketing of produce were found to be statistically insignificant. Contrary to the findings of Achandi (2018), the present study expected access to extension services to improve productivity and technical efficiency of smallholder farmers positively and significantly in Northern Province. This is because access to agricultural technical services can help boost smallholder farmers productivity and technical efficiency by educating them on how to properly utilise their resources (i.e., inputs and technology) (Masunda and Chiweshe, 2015).

2.4 Productivity studies on Zambian agriculture

In the Zambian context, there are a few studies that have directly and specifically analysed the effect of access to financial resources on smallholders' technical efficiency. In addition to the best of the authors knowledge, no similar study has been conducted in Northern province, covering all the major districts. Previous studies have focused on other provinces and small groups of farmers. However, Northern Province is different from other provinces given its unique economic, climatic, and ecological conditions as well as geographic location (Seshamani, 1992). Chiona et al. (2014) employed a translog stochastic frontier model to analyse the technical efficiency of smallholder farmers in the Central Province of Zambia. The author used cross-sectional data from 400 households. Results showed that access to loans, access to extension services, off-farm income and age of household head positively and significantly influenced technical efficiency. Contrary to the findings of this study, the present study expected age of household head to affect productivity and technical efficiency negatively and significantly. This is because younger farmers are likely to be more energetic and can therefore spend more time working on the farm than older farmers. Younger farmers are also likely to have better access to agricultural technical information through the use of mobile applications and other forms of technology (Okoye, et al., 2016; Girabi and Mwakaje, 2013).

Focusing only on Masaiti district, which is one of the districts in the Copperbelt Province of Zambia, Musaba and Bwacha (2014) examined the technical efficiency of smallholder maize producers using a Cobb-Douglas stochastic frontier production function model. Using this methodology, the authors found that maize production was significantly affected by area planted and fertiliser. Seed and labour variables were insignificant, with negative signs. This was contrary to the expectation of the study. The authors attributed the unexpected results to the possibility the farmers in their sample could have not used improved seed varieties. In terms of labour, the authors mentioned that sampled households were characterised by large household size, with each member able to supply more labour. Meaning that any increase in labour input could potentially reduce technical efficiency. This explanation is contestable given the fact that both labour and seed were statistically insignificant. Further, the inefficiency model results revealed that access to fertiliser, age of a farmer, cooperative membership and farm size were significant and positively affected technical efficiency. Given the importance of fertiliser, it could have been useful for the study to also consider the effects of access to farm input support programme (FISP) on the technical efficiency of smallholder farmers. The study could have further considered the impact of access to credit on farmers productivity and technical efficiency. Having access to credit could further have explained the source of fertiliser, especially for those farmers who perhaps were not under the farmer input support programme. In addition, the study found that the education level of the farmer, crop rotational practices and the use of different seed types had negative and significant impact on technical efficiency. Access to extension services was found to be statistically insignificant. This is contrary to the expectation of this study.

Mukwalikuli (2018) used cross-sectional data from 120 smallholder rice farmers in Lukulu—one of the districts in the Western Province of Zambia. The author developed a stochastic frontier Cobb-Douglas production function to determine their technical efficiency. Results of the inefficiency model showed that planting method and number of cattle owned significantly and positively improved technical efficiency. Access to credit and access to extension services were only positive and significant at 10%. This contrasted the expectation and empirical evidence that both access to credit and extension services could strongly improve productivity and technical efficiency (Girabi and Mwakaje, 2013; Abate, et al., 2016; Melkani, et al., 2019; Koricho and Ahmed, 2021). Age of household head, gender of household head and marital status were statistically insignificant.

Ng'ombe and Kalinda (2015) used a stochastic frontier analysis (based on both the half-normal and exponential model distributions) to assess the technical efficiency of smallholder maize producer that practiced minimum tillage. The authors used Zambia's nationally representative cross-sectional data of 160 smallholder farmers who practised minimum tillage. Results indicated that access to loans, level of education of household head and square of household size did improve technical efficiency; while off-farm income, marital status (1=if single) and distance to vehicular road worsened the technical efficiency of smallholder farmers. Household size, belonging to farmer association, access to fertiliser, distance to input market, distance to product market, livestock holding, access to extension services and gender of household head were statistically insignificant. The insignificance of access to extension services and access to credit are contrary to the priori expectation. Ng'ombe (2017) applied a stochastic meta-frontier and region-specific stochastic frontiers to estimate the technical efficiency of smallholder maize production in Zambia. Results revealed that some regions in the country were more technically efficient than others while those with technical efficiency values above 90% operated further below the potential output compared to those with moderate technical efficiency values. Stochastic meta-frontier parameter estimates showed that land, square of land, square of capital, square of fertiliser and the cross-products of labour and capital. Labour and land, labour and fertiliser, land and capital, land and fertiliser and fertiliser and capital were statistically significant. Capital, labour, the square of labour and the square of capital were statistically insignificant.

The present study will contribute to the existing literature in various ways. First, to the author's knowledge, this is the first study that is using the translog stochastic frontier production function to assess the impact of access to credit on technical efficiency of smallholder maize farmers in Northern Province, Zambia. As mentioned above, previous studies focused on other provinces (Musaba and Bwacha, 2014; Mukwalikuli, 2018; (Chiona, et al., 2014). Northern Province is different from these other settings in many respects. Secondly, the study will improve on Ng'ombe (2017) [which used nationally representative panel data for 2000 and 2008] by using a more recent and updated data from 2015 RALS. In addition, more empirical work is needed to assess smallholders' performance and efficiency constraints, especially following the regime change in 2011 (when the Movement Multiparty Democracy [MMD] lost power to the former ruling part, Patriotic Front [PF]).

Further, under the Patriotic Front government the expenditure on agriculture and number of farmer input support programme (FISP) beneficiaries was increased, and therefore, it is necessary to assess the impact that these changes have had on smallholder crop farmers. Finally, exploring the effect of FISP, extension services, distance between homestead and farm, gender of household head, age of household head, level of education of household head and the possible interaction between them can provide policy makers and decision makers with more elaborate pathways of the effects that these variables have on technical efficiency. This study, therefore, sort to analyse the factors influencing the technical efficiency of smallholder maize farmers in Northern Province, Zambia. More specifically, the study aimed to identify the direction and magnitude of effects of access to credit, access to extension services and access to farmer input support programme on technical efficiency, and consequently highlight any potential benefits from access to these institutional factors.

2.5 Chapter Summary

This chapter provided a theoretical overview of efficiency measurement and introduced the conceptual framework utilized in the study. It commenced by emphasizing the primary methodologies employed for evaluating the technical efficiency of smallholder farmers. These approaches included the non-parametric approach (data envelopment analysis (DEA) and the parametric approach (stochastic frontier approach). The present study employed a parametric approach (stochastic frontier analysis) instead of the Data Envelopment Analysis approach. This is because agricultural crop production typically exhibits random shocks (farmers tend to be affected by factors beyond their control such as climatic conditions and inefficiency effects) and because the objective of the study is to measure the contribution of three conditional variables on measured efficiency. This is not possible in the Data Envelopment Analysis approach. The chapter further provided an overview of several empirical studies that have been conducted in Sub-Saharan Africa and thereafter narrows down to the Zambian context. In conclusion, this chapter presented a summary of the policy relevance of the study and contributions to the existing body of literature.

Chapter 3: Data and Methods

This chapter delves into the approach employed to evaluate the technical efficiency of smallholder maize farmers in the Northern Province of Zambia. To commence, a concise overview of the study area, namely the Northern Province, Zambia, is provided. Subsequently, in section 3.2, the sample size and its distribution are presented. Section 3.3 proceeds to describe the distribution of the sample across different districts. In section 3.4, the analysis relies on the Rural Agricultural Livelihood Survey conducted by the Central Statistical Office in 2015, which is outlined. Additionally, section 3.5 provides an overview of the sample distribution according to districts. Lastly, the concluding section of this chapter specifies the production function from which efficiency estimates are derived.

3.1 Brief Geographical Overview of Northern Province, Zambia

The Northern Province constitutes one of Zambia's ten provinces (as illustrated in Figure 3). Geographically, it is strategically positioned, sharing its borders with the Democratic Republic of

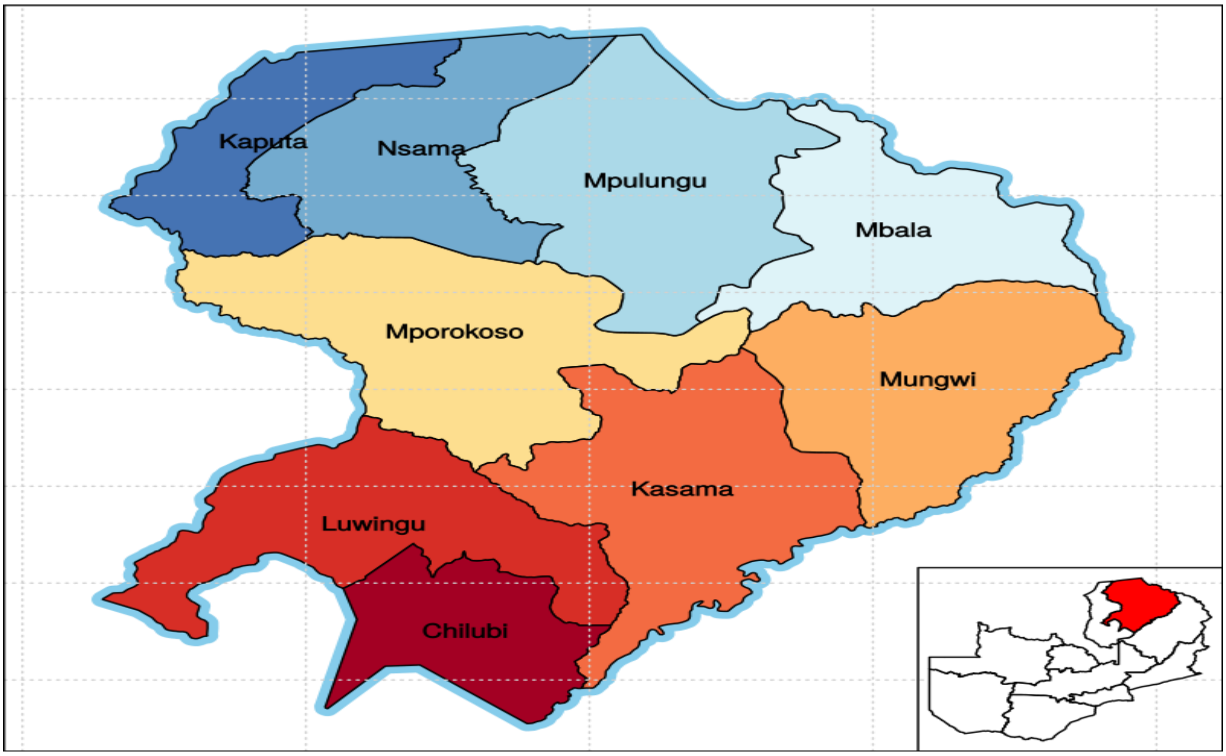

Figure 3: Northern Province, Zambia (Source: Districts of Northern Province of Zambia)

Congo (DRC) to the north, the Republic of Tanzania to the northeast, and providing access to the great lakes region through the presence of Lake Tanganyika (Taylor and Banda-Thole, 2013). Northern Province lies between Luapula Province in the west and Muchinga Province in the east. Until 2011, when Muchinga Province to the southeast was split off from Northern Province, Northern Province was the biggest and most rural province in the country. After the division Northern Province became the third largest in the country covering an area of approximately 77,650 square kilometres. With an estimated 1.3 million inhabitants, the province's population density is less than 19 people per square kilometre (Central Statistical Office, 2015). It is divided into nine districts, with Kasama as provincial headquarters. By road transport, the distance from Kasama to Lusaka and from Kasama to the coast at Dar-es-Salaam is approximately 880 kilometres and 1100 kilometres respectively.

Figure 4: International port at Mpulungu on Lake Tanganyika (Source: Horizon Unlimited)

Fifteen tribes live in the province, with varying cultural practices and traditions. Settlement patterns are influenced by the availability and accessibility of both social services (schools, health services, shops, etc.) and infrastructure (roads and railways). Bemba is the dominant vernacular language (Nelson, 2000). Agriculture is the main economic activity and more than 75% of the population is active in farming and there are no major industries (Taylor, et al., 2013).

Rainfall is high, with most districts receiving an average of more than 1000mm p.a. during the rainy season which lasts from November to March/April (Nelson, 2000). The length of the summer rainy season is 140 to 170 days, which allows rainfed crop production. Normally, during the rainy season, the number of sunshine hours reduces in the province, and as a natural consequence, the potential yield of most crops tends to drop significantly. There is a high rainfall belt stretching from the western part of Mbala to the north-western part of Luwingu districts where the levels of sunshine are below 700 hours. However, agricultural production in other regions in the province is not affected because there is sufficient sunshine even during the farming season (Norwegian Centre for International Agricultural

Development and the International Union for the Conservation of Nature and Natural Resources, 1989). Although not the provincial headquarters, Mbala is the main farming district (Nelson, 2000). Mbala has good access to water, electricity and road infrastructure and is positioned as a gateway to Tanzania, via the border town of Mpulungu.

Mpulungu on Lake Tanganyika is the only international port in Zambia and from it good are exported to Burundi, Tanzania, and the Democratic Republic of Congo. Like Kasama and Mbala, Mpulungu also has good road infrastructure. Through the port, smallholder crop farmers can sell their produce to international markets such as Burundi and the Democratic Republic of Congo.

3.2 Sample Size and Distribution

This study analyses the Northern Province subsample of RALS (2015).

Table 1: Sample size and response rates by province

Province	**Sample Size**	**Observations**	**Response Rate (%)**	**%New hh**
Central	840	650	77.3	0
Copperbelt	680	549	80.7	0
Eastern	2340	2063	88.2	14.5
Luapula	840	692	82.4	0
Lusaka	520	446	85.7	30.8
Muchinga	860	717	83.4	20.9
Northern	**1000**	**791**	**79.1**	**0**
North-Western	640	516	80.6	0
Southern	1040	893	85.9	0
Western	760	617	81.2	0
National	9500	7934	83.5	6.9

Source: CSO, et al., 2016, p.15)

At the national level, the Rural Agricultural Livelihoods Survey (RALS) conducted in 2015 utilized a two-stage stratified sample design based on Zambia's 2010 Census of Housing and Population. The survey included a sample size of 7,934 households, randomly selected to ensure representativeness. In the first stage, primary sampling units were identified as one or more standard enumeration areas with a minimum of thirty agricultural households, defined by census sketch maps. The second stage involved listing all households in selected enumeration areas and selecting agricultural households. Stratification was performed based on factors such as total cultivated area, unique crops, and income sources. To distribute representation evenly, a systematic sampling technique was applied, selecting twenty households from each stratum (A, B, and C) within every standard enumeration area. This rigorous methodology aimed to capture the diversity of agricultural households while considering cultivation area, crop variation, and income sources (for further details see Rural Agricultural Livelihoods Survey 2015 Survey Report).

Northern Province has a total number 50 standard enumeration area and a total of 791 households were interviewed in 2015. The province had one of the highest numbers of standard enumeration areas, ranking third after Eastern (117) and Southern (52). The attrition rate was 8.7% relative to 2012. This was explained by a few households that had shifted to other places from the study area. As opposed to covering the entire ten provinces of Zambia, this study only focused on Northern Province using cross-sectional data from the RALS 2015. Specifically, the study utilised data from the agricultural households that were reinterviewed in 2015. Of the one thousand households in fifty enumerator areas in this province, 791 were resampled in RALS (2015). However, after adjusting for missing observations, the sample was reduced to 634 complete observations (a respectable 80.2% response rate) and the same were used in analysis.

3.3 Rural Agricultural Livelihood Survey

Data for this study was drawn from nationally representative household survey of smallholder farmers in Zambia. The Rural Agricultural Livelihoods Survey (RALS) was conducted between June and July 2015 by Indaba Agricultural Policy Research Institute (IAPRI) in collaboration with Zambia Statistical Agency (formerly called Central Statistics Office) and the Ministry of Agriculture and Livestock. At the time RALS was the most comprehensive and nationally representative (covering all the ten provinces of Zambia) rural survey for small and medium-scale farming sector in Zambia to date. The RALS is primarily designed to provide comprehensive information that is useful to policy makers as they attempt to formulate relevant policies. The survey presents a broader picture of the state of livelihood activities and outcomes among the rural smallholder farmers. It further makes it possible for Zambian policy makers to accurately monitor the trends in the country's agricultural and rural sectors or assess the progress toward national policy objectives.

3.4 Sample Distribution by District

The 634 complete observations used for this study were drawn from all the eight major districts of Northern Province, Zambia. This ensured that the sample was a good representation of the smallholder maize farmers in the province.

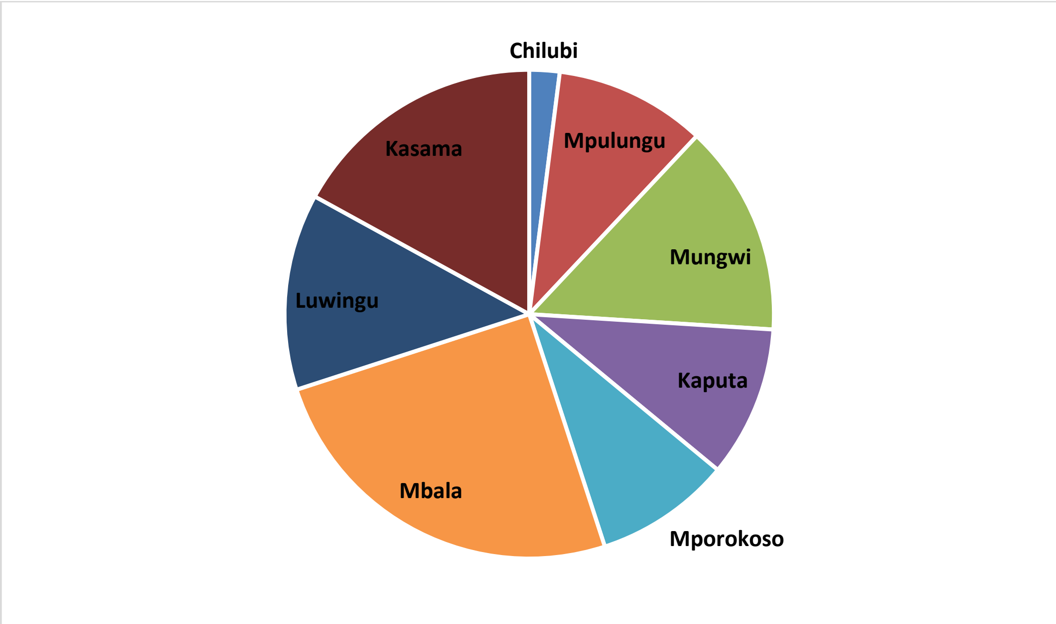

Figure 5: Sample percentage distribution by district (Source: CSO, et al., 2016)

Mbala district had the highest number of responses (25%), followed by Kasama (17%), Mungwi (14%), Luwingu (13%), Mporokoso (9%), Mpulungu (10%) and Kaputa (10%). The district with the least number of observations is Chilubi (2%).

3.5 Model specification

This study employs the stochastic frontier analysis framework to estimate technical efficiency of crop smallholder farmers in Northern Province. A production function is used to benchmark technical farm efficiency, and in the tradition of Battese and Coelli (1995) these deviations as a linear combination of farm and farmer characteristics in the inefficiency sub-model of this joint specification. The farm-level prices needed to measure allocative efficiency have not been collected.

3.5.1. Stochastic Production Function

The formulation of the stochastic frontier model can be specified for cross sectional data in terms of a stochastic production function which was first proposed by Aigner, et al. (1977) and Meeusen and Broeck (1977) as shown below:

$Y_i = f(X_{ik}, \beta) + v_i - u_i$ (Eq. 1)

where Y_i denotes the value of the production of the ith farm household, such that i = 1, ... n); X_{ik} represents a vector of the associated inputs (land, labour, seed and fertiliser) used by the ith farm household to produce output Y_i; β is a vector of unknown parameters to be estimated; v_i represents the statistical noise (random error term) distributed symmetrically; u_i is the technical inefficiency term (asymmetric error term). The assumption made on the technical inefficiency term is that it is independently and identically distributed (iid) and independent of v_i.

While estimating equation 1 above by Ordinary Least Square (OLS) would provide consistent estimates for the parameters except for the constant (β_0) given the assumption that the expected value of the aggregate error term (ϵ_i) is non-zero, $E(\epsilon_i) \neq 0$, the OLS method fails to provide estimates for farm-specific technical efficiency (Kumbhakar and Wang, 2015 and Hayatullah, 2017). Therefore, since this study aims to measure farm-specific technical efficiencies, the Maximum Likelihood Estimator will be adopted which makes that possible.

3.5.2. Technical Efficiency Term

The u_i estimate is also termed the output-oriented (technical) inefficiency and takes a value on the interval [0,1]. A fully-technically efficient farm household is expected to have an efficiency value of 1, while a fully technically inefficient farmer is expected to have the technical efficiency score equal to zero. In addition, the lower the technical efficiency score, the less efficient a given farm household is (Kumbhakar and Tsionas, 2006).

In line with equation 1, given the x_i input vector and the farm households, the technical efficiency of the i^{th} farm household can be expressed as:

$$TE_i = \frac{Y_i}{Y_i^*} = \frac{f(x_i{:}\,\beta)\, e^{(v_i - u_i)}}{f(x_i{:}\,\beta)\, e^{v_i}} = e^{u_i} \quad \text{[Eq.2]}$$

which denotes the farm-specific technical efficiency as the ration of observed output (Y_i) to the corresponding frontier output Y_i^*, which is the maximum possible level of output the farm household can produce given the current level of technology and in an environment characterised by the stochastic elements described by v_i (Battese and Coelli, 1995; Kumbhakar and Lovell, 2000).

Technical efficiency is only achieved if a farmer can produce the highest possible amount of output from a given set of inputs. Assuming constant returns to scale, Farrell (1957) showed technical efficiency using two inputs, X_1 *and* X_2, to produce a single output, Y. This was depicted by Coelli, et al. (2005) as shown in Figure 2 above (input-oriented efficiency). Line SS' represents the fully efficient farmer, which enables the measurement of technical efficiency possible. Point P represents a technically inefficient farmer. Assuming a farmer is utilising a set of inputs (X_1 and X_2) (This depicted in figure 2 above by point P) to produce a unit of output, then the technical efficiency of that farm would be depicted by distance QP. To achieve efficient production, the inputs (X_1 and X_2) must equivalently reduce the ratio $\frac{QP}{OP}$ (see figure 2 above). *Technical efficiency* (TE) of a farmer is therefore given by TE= $\frac{OQ}{OP}$= [1- $\frac{QP}{OP}$]. Technical efficiency scores range from zero to one. When the technical efficiency score is equal to one, then a farmer is said to be fully technically efficient (as depicted by point Q which is on the efficient frontier). Similarly, when the technical efficiency score is equal to zero, a farmer is said to be fully technically inefficient. On the other hand, Coelli, et al. (2005) noted that if the gradient of the isocost line (denoted by AA') represented the price ratio for the inputs, then the ratio $\frac{OR}{OQ}$ could represent *allocative efficiency* (AE).

3.5.3. Log Likelihood Ratio Test

As Conradie (2019) pointed out, the presence of u_i (inefficiency term), which implicitly suggests the existence of the frontier, is to a larger extent based on prevailing statistical conditions. These statistical conditions must therefore be accounted for using a generalised likelihood ratio (LR) test (Battese and Coelli, 1995; Conradie, 2019). The LR test is expressed as in equation 3 below:

$$LR\ test = -2[LLH_{restricted} - LLH_{unrestricted}] \qquad \text{[Eq. 3]}$$

Where $LLH_{restricted}$ denotes the log likelihood statistic for the restricted model in eq. 1, and the $LLH_{unrestricted}$ is the corresponding statistic produced when the translog production function (equation 5) is fitted. The LR test statistic follows a chi-square distributed with degrees of freedom equating the number of restrictions imposed (Battese and Coelli, 1995, p. 332). The assumed distribution on the inefficiency term (u_i) influences the cumulative density function which is used to compute gamma. Gamma equals to zero characterises a mean response function, regardless of whether $u_i's$ distribution was assumed to be half normal or truncated normal.

3.5.4. Variance Parameter

Using a lambda (λ) parameterisation Battese and Corra (1977) formulated the log likelihood function. The choice of λ was based on the fact that the model is fitted with Front 41. If the model was fitted in Stata lambda parameterisation would have been applied.

More specifically, using gamma parameterisation by Battese and Corra (1977), eq. 2 above can be expressed as follows:

$$\gamma = \frac{\sigma_u^2}{(\sigma_v^2 + \sigma_u^2)} \qquad \text{(Eq. 4)}$$

Where $\gamma = \sigma_u^2/\sigma^2$ and $\sigma^2 = (\sigma_u^2 + \sigma_v^2)$ are variance parameters; γ describes the total variation of observed output (Y_i) from the frontier output (Y^*) that is explained by technical inefficiency. γ ranges from 0 to 1, i.e., [$0 \leq \gamma \geq 1$]. A value of γ close to 1 means that the random component of the inefficiency contributes substantially to the production system. A truncated normal distributional assumption with mean μ and variance ${\sigma_u}^2$ characterises the technical inefficiency parameter, u.

In addition, if γ is statistically insignificant (γ=0), then the model is not a frontier because neither of the error variance can be explained by the farm specific inefficiency effects (Battese and Corra, 1977; Battese and Coelli, 1995; Hayatullah, 2017).

3.6 Empirical Model

As highlighted in chapter 3, the translog functional form is widely used in empirical studies because it meets the second order flexibility condition (Constantin, et al., 2009) and also its logarithmic form makes it possible to capture inefficiencies by using an additive term and therefore simplifying the estimation. Equation 5a below presents the general estimating equation used to fit a production frontier with a translog functional form.

$$\ln y_i = \alpha_0 + \sum_{k=1}^{K} \alpha_k \text{lin} x_{ik} + \sum_{k=1}^{K} \sum_{j=1}^{J} \alpha_{jk} \ln x_{ik} \ln x_{ij} + v_i - u_i \qquad \text{[Eq. 5]}$$

where ln represents the natural logarithm; Y_i denotes total revenue generated from the farm produce by the ith farm household i; K represents the number of inputs used by the farm household, x_{ij} represents a set of inputs (land, labour, seed and fertiliser) used by the i^{th} farm household in the production process; α_k and α_{jk} are (kx1) vectors of unknown parameters to be estimated; ϵ_i denotes the composed error term, $\epsilon_i = v_i - u_i$, such that $u_i \geq 0$. $v_i's$ represents all the factors (stochastic effects or statistical noise) outside the control of farm household as well as the measurement errors. On the other hand, $-u_i$ is the asymmetrical error term which depicts farm household i's deviation from the best practice frontier and is the basis for calculating the farm household's efficiency level.

These variables are all in natural logarithms and have been mean differenced. By dividing each of the unlogged observations by the unlogged sample mean, the units of measurement are made more convenient for the calculation of elasticities from coefficients produced by the translog functional form. The partial derivative of the production function with respect to a given input contains the logged values of this and other inputs, for example in the two-input case we have:

$$\frac{\partial \ln y}{\partial \ln x_1} = \alpha_1 + \alpha_{11} \ln x_1 + \alpha_{12} \ln x_2$$

Now, if the mean value of $x_1 = 1$ as it becomes as a result of demeaning, the natural logarithm of one is zero, and terms two and three drops away, conveniently simplifying the output elasticity of x_1 to α_1.

3.7 Inefficiency Model

In line with eq. 4 and the assumption made on u_i, the Battese and Coelli (1995) inefficiency model is expressed as follows:

$$-u_i = \delta_0 + \sum_{i=1}^{3} \delta_i Z_i + w_i \qquad \text{(Eq. 6)}$$

where (u_i) is the inefficiency, z_i is the vector of exogeneous (inefficiency) variables (access to credit, access to extension services, access to farmer input support programme, distance between homestead and farm, gender of household head, age of household head and education level of household head) that are likely to affect the efficiency of farm households; δ_i are the parameters to be estimated; and finally, the inefficiency of the error term is given by an independently and identically distributed error term $\omega_i \sim (0, \sigma_w^2)$. Since the dependant variable in eq. 5a is the technical inefficiency, a farm-specific variable associated with positive (negative) coefficient will have a negative (positive) effect on technical efficiency (Kumbhakar and Wang, 2015).

3.8 Variable Description

A one-stage stochastic frontier with technical efficiency effects model in the tradition of Battese and Coelli was specified to explore the contribution of access to credit to the efficiency of smallholder production in Northern Province, Zambia. The production function is for crop production, typically of casava and maize with a small amount of cash crops. Livestock is scarce in these communities due to diseases outbreaks, although the climate, water and the veld is conducive dairying.

The dependant and independent variables used for this study are as follows:

Yield: Yield describes the total harvest per farm. Yield of the following crops were considered in this study: Maize, sorghum, millet, soya beans, mixed beans, sweet potatoes, rice, sunflower, groundnuts and Bambara nuts. Bambara nut is a legume that is related to cowpeas and peanuts. They are mostly hand harvested and the nuts are dried. Since the quantity of home consumption is not included in the dependent variable, the conclusion of this study refers explicitly to the efficiency of surplus production. The exact phrasing of the question used is presented in Appendix 1.

Land: Land is an essential input of smallholder production. The variable here measures the combined size of the three production systems above and includes all plots cultivated by the household in hectares. Measured in hectares, the size of land cultivated was hypothesised to have a positive significant impact on the productivity of farm households.

Labour: In this study, labour was calculated in terms of the number of days each household member contributed to the household's farm in 2013/14 growing season (The exact phrasing of the question used is presented in Appendix 1). The growing season ranges between October and April. Labour only consisted of family members' labour days. Data for hired labour was not available.

Seed: Some farm households purchased seeds on their own while others accessed it through the government's farm input support programmes. The quantity of seed in this study is a combination of seeds that were accessed through government's support, seeds saved from own production, cash purchase from private trader/retailer as well as direct commercial exchange or barter. Farmers acquired seeds from the government either direct from farmer input support programme or through farmer cooperations. Other government sources included Ministry of Community Development, Mother and Child Health through food security packs. Data detailing the quantity of seeds acquired through government support was not separately available. Cassava production in Northern Province does not require actual seeds, and so farmers planted stalks from existing crops. These cassava stalks are what some local farmers call seeds, but they not actually seed.

Fertiliser: Inorganic fertiliser is measured in kilograms. The inorganic fertiliser considered in this study is the one used by rather than the one the farm household had access to (The exact phrasing of the question used is presented in Appendix 1). Most farm households used fertiliser primarily to produce maize. Crops such mixed means, cassava, sorghum, millet, soya beans and sweet potatoes do not require fertilizer. Some farm households purchased fertiliser on their own while others accessed it through the government's farm input support programmes. The dataset for this study combines the two sources of fertiliser. Data detailing the quantity of fertiliser acquired through government support and through private purchase was not separately available.

Access to credit: This is a dummy variable =1 if a farm household received any form of credit to buy crop inputs and =0 otherwise. Credit overcomes liquidity constraints enabling smallholders to adopt modern inputs (fertiliser, high-yield seeds) and thereby it increases the level of efficiency of smallholder production, the focus of this study. Access to production credit is therefore hypothesised to help increase efficiency of crop smallholder farmers in Northern Province (Girabi and Mwakaje, 2013; Abate, et al., 2016; Melkani, et al., 2019; Koricho and Ahmed, 2021) .

Access to extension services: This is a dummy variable which is equal to 1 if farm households had access to agricultural technical services and zero otherwise. Relevant Technical services, as drawn from Zambia's 2015 rural agricultural livelihoods survey (RALS), include "information on topics such as minimum tillage using planting basins (potholes), minimum tillage using ripping, leaving crop residues in the field and incorporating it into soil, rotating cereals with legumes or nitrogen-fixing crops, intercropping cereals with legumes" and growing "crops that are well suited to soil and weather conditions", among others (CSO, et al., 2016). Only 30% of surveyed households has access to extension services (CSO, et al., 2016). It was hypothesised that having access to agricultural technical support services would increase the productivity and efficiency of farm households (Tchale and Sauer, 2007; Dube and Guveya, 2014; Koirala, et al., 2015).

Access to Farm Input Support Programme: Access to inputs (improved seed and fertiliser) is one of the most important factors that determine the quantity of production of crops among smallholder farmers. Smallholder farmers who have access to improved seeds are expected to be more efficient than those who do not. This is because the use of modern inputs, like improved seed varieties improves efficiency (Melkani, et al., 2019; Koricho and Ahmed, 2021). Instead of sowing a kilogram of traditional seed, if a farmer sows one kilogram of hybrid seed, the hybrid seed plants grow more vigorously, responding better to rainfall and fertilizer applications, resulting in greater yield. Similarly, the use of fertiliser is expected to improve efficiency. By adding the fertiliser input adds the correct amount of potassium in the root zone so that plants can grow optimally. Farmers who do not have access to fertiliser often opt for inefficient methods such as Chitemene which involves the cutting down and burning of trees. It was therefore hypothesised that having access to farmer input support programme would increase the productivity and efficiency of farm households (Tchale and Sauer, 2007; Dube and Guveya, 2014; Abate, et al., 2016; Mariyono, 2019).

Education: In this study, education was calculated in terms of the number of years the household head spent in formal education. The inclusion of education variable is premised on the idea that smallholder farmers that have attained at least basic education could make well-informed production decisions compared to those farmers that did not attain any level of formal education. Therefore, this study hypothesised that the household head's level of education would increase the productivity and efficiency of farm households (Koirala, et al., 2015; Matsvai, et al., 2020).

Age: Age was calculated in terms of number years of the household head. The sample average age was calculated to be 47 years, with a maximum of 89 years. The average age for women was 52 years compared to 46 years for men. On average, female farmers are older than their male counterparts. As a possible proxy for experience, older farmers were expected to have acquired better technical skills and farming expertise compared to younger ones. Measured in years, age of household head was therefore hypothesised to have a positive and significant impact on the productivity and technical efficiency of farm households. It was expected that younger farmers would be more technically efficient that older farmers (Okoye, et al., 2016; Girabi and Mwakaje, 2013).

Gender: This is a dummy variable which is equal to 1 if farm household is headed by a male and zero otherwise. This study expected male-headed households to be more productive and technically efficient than the female-headed households. This is because women have an additional role of looking after children and performing other household duties. In most cases, this it is a cultural requirement that women be the ones to look after children. Gender (1=male, 0=female) was hypothesised to have a positive significant impact on the productivity and technical efficiency.

Distance: In this study, distance between homestead and farm was calculated in kilometres. The average distance was found to be 2.7 kilometres, with a maximum of 40 kilometres. Longer distance from homestead to the field was expected to reduce productivity and technical efficiency. The explanation for this is straightforward. If a farmer lives farm away from his / her fields, a portion of the day is spend commuting, and this tightens the labour constraint, causing poorer outcomes.

3.9 Maximum Likelihood Estimator (MLE)

There are several methods that could be used to estimating the stochastic frontier model. The choice of method is a function of which assumptions are made concerning the distribution of the error components (Greene, 1980; Hayatullah, 2017). Two of the methods identified in literature to measure technical efficiency without necessarily having to impose assumptions on the distribution of the inefficiency component of composite error term are the Corrected Mean Absolute Deviation (CMAD) and the Corrected Ordinary Least Square (COLS) (Kumbhakar and Wanga, 2015, Hayatullah, 2017). These two approaches, however, assume that the variation in inefficiency is the only cause of the model's randomness. Both the COLS and the CMAD furthermore assumes that the frontier is deterministic in nature (Kumbhakar and Wanga, 2015)

The use of the Maximum Likelihood (ML) approach is sensitive to the assumptions made concerning the distribution of the inefficiency and random errors (Greene, 1980; Battese and Coelli, 1995; Battese and Cora, 1977). Once these assumptions are imposed, the log-likelihood function of the model is obtained, and numerical maximisation procedures are thereafter employed to derive the maximum likelihood estimates of the model parameters. The maximum likelihood estimate of an unknown parameter is defined as the numerical value of a given parameter of interest that maximises the probability of drawing a particular cluster of observations (Green, 1980; Lee, 1983; Hayatullah, 2017). The first derivative results are thereafter equated to zero. However, given that the first order conditions cannot be solved mathematically for parameters and at the same time they are highly non-linear the likelihood function is maximised using iterative optimization method (Green, 1980; Lee, 1983; Kumbhakar and Wang, 2015; Hayatullah, 2017).

3.10 Data analysis: Software

The study uses “FRONTIER version 4.1” (a computer programme for stochastic frontier production and cost function estimation developed by Tim Coelli) to estimate the translog stochastic frontier and the subsequent likelihood ratio test (Battese and Coelli, 1988, 1992, 1995).

3.11 Chapter summary

The chapter has discussed the geographic location of the study area and presented the methodology used to achieve the objectives of this study. The study employs a stochastic frontier analysis model to estimate the technical efficiency of smallholder maize farmers in Northern Province. In the production function, the dependent variable is maize harvested (in hectares), and the independent variables are land size measured in hectares, labour days, seeds and fertiliser used per farm. In the technical inefficiency model, the farm household specific independent variables are access to credit, access to farmer input support programme, access to extension services, distance, age of household head, education of household head, gender of household head and household size.

Chapter 4: Results and Discussion

Chapter four of the study provides a summary of the results obtained from estimating the Cobb-Douglas and translog frontier production functions, with the detailed specifications explained in chapter three. The chapter begins by introducing the agriculture context in Northern Province, Zambia, followed by presenting descriptive statistics. It then discusses the specification tests conducted and presents the main results using Tables 4 and 5. The chapter concludes by presenting and analysing the technical efficiency scores of the sampled farm households, offering insights into their performance.

4.1 Agriculture in Northern Province, Zambia

The diversity in socio-economic and agro-ecological conditions in the region produces complex land use arrangements. The Rural Agricultural Livelihood Survey (RALS, 2015) divided farmers into three size classes of 1-2.5 ha, 2-5ha and 5-15 ha. Most smallholders fall into the smallest class, with 26% in the medium and 7% in the large size classes. At this scale hand tools are sufficient and family labour the main labour force. With seed and fertiliser obtained through farmer input support programme, smallholders can cultivate an average of 0.97 hectares of land. RALS (2015) further shows that 85.17% of the farmers cultivated one field, while 14.83% cultivated several fields. The highest number fields cultivated per farm household was 8. As much as 80% of farmers who cultivated more than one field reported having access to credit that the author believes could have been used to acquire inputs for the second, third and fourth fields. Approximately 90% of the farmers that cultivated several fields had access to seed and fertiliser through farmer input support programme.

Figure 6: Maize Ibala , Northern Province, Zambia (Source: ZNBC)

RALS (2015) shows that most respondents cultivate virgin ground first in cassava, which is an inferior food crop, and then rotate the land into cash crops like beans, maize, or groundnuts (CSO, et al., 2016). There are three main methods of cultivation, namely *chitemene* (Figure 6), *fundikala* and *ibala*. These methods differ mainly in how they achieve soil fertility in the absence of inorganic fertiliser, which is an uncommon input in smallholder farming in Northern Province, Zambia.

Figure 7: Burned Chitemene field (Ubukula) (Source: Mapio.net)

In the past, *chitemene* (slash and burn) shifting cultivation system was the dominant land-use method but as the population size increased, households with less land began to use their resource more intensively. In the *chitemene* system potash and charcoal released by burning enrich the soil and improves soil pH (see figure 7). Trees and brush are cleared early in the dry season and burnt towards the end of the dry season, awaiting the first rains in October.

In the *fundikila* system composting rather than burning improves the organic content of soils. This method is most suited to areas that have been burnt before. In these clearings, the sod is turned into "windrows" or ridges at the beginning of the dry season and left to compost for six months. When the rains are imminent the organic rich ridge soils are either spread to cover the full area or maize or cassava is planted directly onto the ridges. In most cases, finger millet is planted among the maturing maize and cassava plants and harvested in the rainy season.

Ibala refers to intercropped home gardens. Most of the crops are grown on compost ridges, although when fertiliser is available, the ridges are flattened for the growing of finger millet. Almost all smallholder farmers in the province have *Ibala* or *amabala* (gardens). Sometimes farmers make *amabala* fields near perennial streams for irrigation purposes. A variety of vegetables like rape, cabbage and tomatoes are grown together with beans and maize. The nearer the field to the homestead the lesser the amount of labour is required for transportation of the produce from the field. While this permanent production system close to the homestead is very convenient it is the most vulnerable to soil degradation from acidification and weed encroachment, which are easily avoided by rotating outlying fields (Pottier, 1988). Continuously cultivated maize fields wear out within five years.

Cassava is the most prevalent food crop in Northern Province, followed by maize, groundnuts, and dried beans. Cassava is easy and cheap to grow and does not require fertiliser or certified seeds (Nelson, 2000). Maize, groundnuts, and dried beans produce large yields from improved seeds than from seeds kept back from the previous harvest. These crops also benefit from the application of chemical fertilisers. Minor crops include millet, sorghum, rice, soybeans, cow peas, sunflower seeds, and sweet potatoes. A variety of vegetables are grown as are tree crops such as avocados, oranges, mangoes, and coffee. Staples in the local diet include maize, cassava and people aspire to also consume rice (Taylor and Banda-Thole, 2013). Surplus foods are sold into the market economy, at a fixed price to the Food Reserve Agency in the case of maize or to other households within the community. It is not always the case that farmers would sell their produce for money; sometimes farmers barter their produce for other items such as clothes, shoes or even livestock (Nelson, 2000).

In the Northern Province, it is common for merchants who specialize in clothing and other commodities to visit rural communities, particularly during harvest seasons, to engage in bartering. They offer their goods in exchange for maize or mixed beans. For instance, if a household has grown maize, they can trade a portion of their harvest for clothing or other household necessities. This practice is prevalent due to limited direct market access for smallholder farmers in the province, leading them to rely on these middlemen or merchants who often exploit them (White, et al., 2005). One significant issue is that smallholders frequently lack knowledge about the true value of the items they exchange for their agricultural produce.

In the rural areas of the Northern Province, cassava and maize serve as the fundamental dietary staples. These crops are meticulously processed, transforming them into flour by removing the husks and obtaining a refined white powder. In the local Bemba language, maize flour is known as "*Ubunga bwa Mataba*," while cassava and millet flours are referred to as "*Ubunga bwa Tute*" and "*Ubunga bwa Male*," respectively. During periods of scarcity, households often rely on cassava and millet meals as maize production requires significant investment in seeds and fertilizers. The preparation of these dishes involves blending the flour with warm water and heating it to create a thick, porridge-like consistency. Typically, this thick porridge is accompanied by cooked vegetables, primarily cassava and bean leaves, complemented by groundnuts. However, due to the presence of tsetse flies, which transmit trypanosomiasis (African sleeping sickness), livestock such as cattle and goats are not commonly raised, resulting in scarce availability of meat.

To supplement their meals, many households incorporate *ubwali* (maize meal) into their diet and also consume insects like caterpillars, as well as a diverse array of wild plants collected throughout the year. Unfortunately, a concerning reality is that most rural households can only afford a single main meal per day, which falls short of meeting adequate nutritional needs (Mwanamwenge and Harris, 2017). Despite a relatively better food supply during the harvest season in the Northern Province, it remains insufficient to adequately address the requirements of the majority of households. Excess crops are traditionally stored in "*Ubutala*," which are storage facilities made from wood and grass.

The Northern Province holds the position of the fourth largest producer of maize nationwide in terms of marketable surplus. Additionally, it excels in beans production, ranking first, and secures the second spot in groundnut and cassava production, as reported by the Zambia Central Statistics Office in 2014. This implies that enhancing the productivity of smallholder agriculture in the Northern Province would have a direct impact on national food security and contribute significantly to local economic development. What is more, given the predominantly rural nature of the province and the limited land area currently dedicated to commercial agriculture, any growth achieved is likely to be fairly distributed among the most impoverished individuals. Consequently, such growth would lead to improved livelihoods for the local population.

4.2 Sample Characteristics

This section presents the sample descriptive statistics. Table 2 summarises the farmer and household characteristics that will feed into the maize production function and the inefficiency sub-model that explains the observed variation in calculated farm efficiency. Table 3 contains information on the inputs and outputs. Government support for smallholders, in the form of the Farmer Input Support Programme, or FISP input packs, extension services and access to credit is summarised in Table 3.

Smallholder agriculture serves as the prevailing vocation and lifelong pursuit in the Northern Province of Zambia, where limited access to secondary and particularly tertiary education severely constrains alternative opportunities (White et al., 2005). Within the most impoverished rural households, a staggering 81% of children abandon formal schooling to assist with farming activities. This approach highlights the paramount importance of achieving food self-sufficiency in the remote rural areas of Zambia, coupled with the scarcity of non-agricultural jobs that necessitate formal education. At the tender age of 12, children become actively involved in harvesting, while both girls and boys assume responsibilities such as ploughing and planting from the age of 14. In the sampled population, the age range of farmers spans from 23 to 89 years, with a mean age slightly surpassing 47.49 years. Most households examined in this study are helmed by males, accounting for 85% of the sampled households, leaving a mere 15% under female leadership. Regarding household size, the distribution ranges from 1 to 15 members per household, with an average of 6 individuals. Notably, the household composition includes children aged six and above. This portrayal accurately reflects rural households and families, not solely within the Northern Province, but throughout Zambia as a whole.

Table 2: Farm Household Characteristics (n=634 households)

Variable	**Description**	**Mean or Number**	**Standard Dev.**	**Min**	**Max**
Household size	Total number of household members	6.749	2.350	1	15
Gender	Male heads of household	539			
	Female heads of household	95			
Age	Age of household head in years	47.492	14.017	23	89
Education	Years of schooling of household head	6.409	3.418	0	17
	No schooling	44			
	Primary schooling	380			
	Secondary schooling	197			
	Tertiary schooling	13			

Source: Author's Own Computations Based on RALS 2015 Data

Older household heads in the sample are associated with larger household sizes compared to younger heads of households. The average number of years spent in formal education by heads of household is just over 6 years. 60% of the sampled households attained primary education, with only 2% of heads of household attaining tertiary education. Male heads of household in the sample are better educated than females. This study only considered gender (male=1) of household head, age (in years) of household head and education of household head were considered in the model.

Table 3 provides a summary of the descriptive statistics for maize production, revealing that the average household in the sample produced slightly over 3 tons of maize grain during 2014/5.

Cultivation areas ranged from one-tenth of a hectare to nine hectares, with an average yield of 3.6 tons per hectare achieved by households with the largest crop on the largest area. In comparison, commercial maize yields in Zambia surpass 15 tons per hectare, indicating significant potential for productivity improvement among smallholder farmers. Notably, the typical maize plot requires nearly 200 man-days per season for essential activities, with an average sowing density of 21.16 kg of seed per hectare and a typical fertiliser application of 342.09 kgs of both basal dressing and top-dressing fertiliser. These findings highlight the scope for enhancing productivity in the smallholder sector, considering the considerable gap between current yields and the commercial benchmark, as well as the labour-intensive practices and fertilizer usage observed.

Table 3: Farm Output, Inputs, and Institutional Factors (n=634 households)

Variable	Description	Mean or Number	Standard Dev	Min	Max
Output	Total harvest of maize (Kgs)	3,140.83	4,912.76	8	77,395
Land	Total area cultivated (ha)	0.97	1.03	0.03	9
Labour	Total labour days	196.13	98.19	20	600
Seed	Total kgs of seeds used	21.16	22.97	0.50	220.40
Fertiliser	Total kgs of fertiliser used	315.80	382.49	0	3600
Credit	Access to credit (yes=1)	51			
Extension services	Access to extension services (yes=1)	313			
FISP	Access to farmer input support programme (yes=1)	363			

Source: Author's Own Computations Based on RALS 2015 Data

Table 3 illustrates a notable disparity in access to production credit within the sample. Merely a small proportion of the participants had such access. Interestingly, 86.27% of the recipients belonged to male-headed households, whereas only 15.69% were from female-headed households. According to CSO, et al. (2016), most of the credit or loans were obtained from informal sources such as friends, relatives, or moneylenders (e.g., *kaloba*), constituting 49.02% of the total. Community-based savings groups accounted for 21.57%, while farmers' unions or cooperatives made up 5.88%, and NGO/faith-based organizations/churches constituted 5.88%. Other sources of credit or loans included commercial banks (3.92%), the Zambia National Farmers Union (ZNFU) Lima Credit Scheme (1.96%), microcredit institutions/community credit schemes (1.96%), out-grower schemes (1.96%), and input credit from private companies (excluding out-grower schemes) (1.96%).

Among the sampled farm households, access to extension services was reported by as many as 49.37%. Out of this proportion, 84.31% represented male-headed households, whereas only 13.73% were female-headed households with access to extension services. Additionally, over half of the sampled households had access to the farmer input support program. Within this group, 86.78% comprised male-headed households, while a mere 13.77% consisted of female-headed households with access to the farmer input support program.

4.3 Functional form for the stochastic production function

Table 4 and 5 present the empirical estimates of a Cobb-Douglas and translog stochastic frontier production function model, respectively. These tables also display the associated inefficiency effects models, which aim to identify factors influencing the productivity and technical efficiency of maize smallholder farmers in the sample. The results of these two models are discussed individually, starting with the Cobb-Douglas model. Additionally, a formal specification test is conducted to examine the desirability of imposing the Cobb-Douglas restriction on the production function.

The estimated Cobb-Douglas production frontier parameters presented in Table 4 exhibit the anticipated signs and display statistical significance. The returns to scale (RTS) value of 1.19 for the dependent variable in the production function indicates that a unit increase in input levels would lead to a more than proportional increase in total maize output. Consequently, further inputs are expected to yield an output increase greater than proportionate, suggesting that farmers should be encouraged to expand their cultivation area and utilize more purchased inputs. In the Cobb-Douglas framework, the coefficients associated with input variables, namely land, labor, seed, and fertilizer, are interpreted as output elasticities. Empirical findings reveal that land use (0.49) is the primary driver of output variation, followed by seed (0.43) as the second most influential input. Fertilizer use (0.12) accounts for the least variation in output, with labor days (0.16) ranking slightly higher. This ranking can be attributed to the fact that individual farmers have greater control over the size of their cultivated fields compared to the amount of fertilizer applied, which is determined by the input package.

With less variation in fertilizer use observed within the sample, this variable has less explanatory power in accounting for output variations. The positive coefficients associated with cultivated area (land), fertilizer, seed, and labor days indicate that increasing the levels of these inputs leads to higher maize production. This finding demonstrates that the Cobb-Douglas production function exhibits desirable behaviour. These results align with the empirical findings of Conradie and Genis (2020), who similarly found that increasing fertilizer, seed, and labor significantly enhanced crop output. The outcomes surpass those reported in similar studies conducted in Zambia. For instance, Musaba and Bwacha (2014) found labor and seed to be insignificant, while Ng'ombe and Kalinda (2015) discovered that labor exhibited a negative effect despite being significant, and capital did not significantly contribute to output. Only fertilizer and seeds were found to be significant with expected signs. Ng'ombe (2017) found that only fertilizer, seed, and capital positively influenced output, while labor was not statistically significant.

Table 4: Estimates of the stochastic Cobb-Douglas model with inefficiency effects

	Cobb-Douglas Model			
Variable	**Coefficient**	**Std. error**	**T-test**	**Significance**
Constant	5.554	0.298	18.631	***
Land	0.491	0.067	7.346	***
Labour	0.158	0.042	3.718	***
Seed	0.427	0.068	6.326	***
Fertiliser	0.116	0.012	9.375	***
Constant	1.135	0.485	2.341	**
Credit	-1.136	0.621	-1.831	*
Extension services	-1.755	0.486	-3.614	***
FISP	-2.280	0.596	-3.826	***
Distance	0.053	0.025	2.115	**
Male Gender	-1.133	0.363	-3.119	***
Age	-0.020	0.008	-2.416	**
Education	-0.509	0.138	-3.679	***

sigma-squared (σ^2)	3.307	0.831	3.978	***
Gamma (γ)	0.961	0.011	87.01	***

***p ≤ 0.01. ** p≤ 0.05, *p ≤ 0.10, σ^2=total error variance, $\gamma = \sigma_u^2 / (\sigma_u^2 + \sigma_v^2)$, All variables are in logs

Table 5 below presents the empirical estimates of a translog stochastic frontier production function model and the associated inefficiency effects model to identify factors that affects the productivity and technical efficiency of the sampled maize smallholder farmers in Northern Province, Zambia. The estimated coefficients of the translog production frontier parameters are positive for land, seed, fertilizer, labour, labour squared, fertilizer squared, the cross product of land and labour, cross products of land and seed, cross product of land and fertilizer, cross product of labour and fertiliser, but negative for land squared, seed squared, the cross product of land and fertiliser, cross product of labour and seed as well as the cross product of labour and fertiliser.

Table 5:Estimates of the translog stochastic frontier model with inefficiency effects

	Translog Model			
Variable	**Coefficient**	**Std. error**	**T-test**	**Significance**
Constant	0.261	0.054	4.853	***
Land	0.411	0.072	5.676	***
Labour	0.147	0.042	3.524	***
Seed	0.272	0.068	4.005	***
Fertiliser	0.316	0.043	7.426	***
Land x Labour	0.228	0.127	1.788	*
Land x Seed	0.500	0.225	2.217	**
Land x Fertiliser	-0.022	0.036	-0.615	ns
Labour x Seed	-0.176	0.118	-1.488	ns
Labour x Fertiliser	-0.005	0.022	-0.238	ns
Seed x Fertiliser	0.005	0.034	0.156	ns

Land x land	-0.297	0.122	-2.442	**
Labour x Labour	0.048	0.049	0.972	ns
Seed x Seed	-0.223	0.118	-1.887	*
Fertiliser x Fertiliser	0.056	0.011	4.859	***
Constant	0.772	0.840	0.919	***
Credit	-1.529	0.479	-3.189	***
Extension services	-1.690	0.226	-7.488	***
FISP	-2.694	0.258	-10.423	***
Distance	0.063	0.020	3.127	***
Male Gender	-1.477	0.269	-5.497	***
Age	-0.012	0.007	-1.683	*
Education	-0.456	0.041	-11.021	***
sigma-squared (σ^2)	3.382	0.389	8.694	***
Gamma (γ)	0.967	0.004	259.037	***

***p ≤ 0.01. ** p≤ 0.05, *p ≤ 0.10, σ^2=total error variance, $\gamma = \sigma_u^2 / (\sigma_u^2 + \sigma_v^2)$, All variables are in logs

The returns to scale estimate from the levels data is 1.24. The land coefficient (0.41) indicates that land accounts for the biggest source of variation in output followed by fertiliser use (0.32) seed and labour. This is a different order than was produced by the Cobb Douglas specification, but the basic Cobb Douglas coefficients still conformed with theoretical expectations. In the translog model the coefficient on land was 16% smaller than the estimate produced in the Cobb Douglas model and its square term carried a negative and significant sign. This is to be expected in smallholder production where a fixed amount of household labour will lead to less intensive cultivation of larger plots of land. Land's interactions with labour and seed were significant and both coefficients were positive, which indicates complementarity between these inputs.

The technical inefficiency sub-model, which is part of the translog specification, treats the technical inefficiency variable as the dependent variable. In this model, various farm-specific socio-economic and demographic variables (such as age, gender, education, and distance) as well as institutional variables (including access to credit, access to farmer input support programs, and access to extension services) are considered as independent variables. Positive coefficients on these variables indicate a worsening effect on technical efficiency, while negative coefficients suggest an improvement in technical efficiency. The results of the farm inefficiency sub-model, using the translog stochastic frontier model, are presented in Table 5. All the parameters in the model are statistically significant, and most of them have the expected signs.

Notably, when comparing the translog specification to the Cobb-Douglas model, it is observed that the significance of the credit variable has greatly increased. In the translog specification, access to credit is highly significant at the 1% level. The negative sign associated with the credit variable indicates that smallholder farmers in the sample who have access to any form of credit or loan exhibit higher levels of technical efficiency compared to those who do not. This finding aligns with previous studies by Melkani et al. (2019), Koricho and Ahmed (2021), and Matsvai and Tatsvarei (2022), where the authors similarly concluded that access to credit improves the efficiency of smallholder farmers. The above-mentioned studies are comparable to the present study because they focused on smallholder rural farmers and used the stochastic frontier analysis approach. Most of these studies linked high efficiency scores of farmers who had access to production credit to the fact that they can more easily make use of modern farming practices and inputs (improved seeds and fertiliser) (Girabi and Mwakaje, 2013; Abate, at al. 2016; Melkani, et al. 2019).

Koricho and Ahmed (2021) mentioned that smallholders who have access credit can smooth their cashflow and purchase inputs on time. Matsvai and Tatsvarei (2022) submitted that it is easier for smallholder farmers who have access to credit to produce markets and achieve efficient risk management. Khandker and Koolwal (2014) confirmed that farmers who have access to credit are better positioned to handle climate change related risks. It is also possible that smallholder farmers who have access to credit are more productive and efficient because they can overcome technical barriers including access to extension services. It also helps farmers meet farming needs before they harvest their crops and during those times when they are selling their crops. Without access to production to credit, it's possible that farmers would end up selling premature maize (and other crops). Worse still, others may end up selling their produce at very low prices for quick cash. Access to production credit combined with extension services can bring about beneficial market linkages that can help smallholder farmers (Khandker and Koolwal (2014).

The estimated coefficient of access to farmer input support programme is negative and statistically significant. This implies that farmers who have access to farmer input support programme are more technically efficient than those who do not. This result confirms earlier findings by Tchale and Sauer (2007) and Dube and Guveya (2014), which found that the use of modern inputs improved productivity and technical efficiency of smallholders. Additional evidence shows that farmers who have access to agricultural inputs are more likely to increase more land under cultivation (Abate, et al., 2016). It is possible that, instead of sowing a kilogram of traditional seed, if a farmer sows one kilogram of hybrid seed, the hybrid seed plants grow more vigorously, responding better to rainfall and fertilizer applications, resulting in greater yield. Similarly, the fertiliser input adds the correct amount of potassium in the root zone so that plants can grow optimally. Farmers who do not have access to fertiliser often opt for inefficient methods such as Chitemene which involves the cutting down and burning of trees. It was therefore hypothesised that having access to farmer input support programme would increase the productivity and efficiency of farm households.

Access to extension services had a negative coefficient which was significant at 1% level. This result was according to the priori expectation and showed that farmers who had access to extension are more technically efficient than those who do not have access to advice from extension officers. There is no information in the dataset to shed light on the specific nature of information and frequency of encounters with the extension services. However, this finding of the beneficial effect of extension on farm-level productivity confirmed Dube and Guveya (2014) finding that access to extension services improve farmers' crop and animal husbandry skills. Distance between homestead and field was found to have a positive and significant effect on technical efficiency according to priori expectations. This result is consistent with Ng'ombe and Kalinda (2015), in which the authors reported that distance to vehicular road negatively affected technical efficiency. This means that farmers who have fields nearer to their homestead are likely to be more productive and technically efficient. The explanation for this is straightforward. If a farmer lives farm away from his / her fields, a portion of the day is spend commuting, and this tightens the labour constraint, causing poorer outcomes.

Male gender is negative and significant at 1% in both the Cobb-Douglas and translog functional forms. This indicated that male-headed farm households were more technically efficient than those headed by females. The result here is in accordance with Dube, et al. (2017), in which the authors found that female farmers were more technically efficient than male farmers, arguing that female smallholders can just be as efficient as their male counterparts if they are presented with the same level of inputs. The results further refute the finding of Ng'ombe and Kalinda (2015) and Ng'ombe (2017) that the gender variable was not significant in smallholder agriculture. In Northern Province, it is possible that female farmers less likely to adopt more efficient farming methods and purchase modern inputs because of a lack of access to production credit and extension services. Low efficiency scores of female smallholder farmers the in the sample could further be linked to the fact that women in rural areas of Northern Province have extra responsibilities of looking after children and performing other household chores such as cooking and washing. This is especially true in Northern Province where the average household size was found to be 7 members per household.

The coefficient of age of household head is negative but only significant at 10% in the translog model compared to 5% level of significance in Cobb-Douglas model. The negative estimate for age of household head means that older farmers in the sample are more technically efficient than younger farmers. This is consistent with the Musaba and Bwacha (2014) in which the authors found that order farmers were less likely to adopt modern farming practices compared to younger farmers. The results here further contradict the finding of Ng'ombe (2017), in which the author failed to find a statistically significant difference between older farmers and younger farmers in Northern Province. The possible explanation for this is that in smallholder agriculture age of a farmer could be a proxy for experience. This entails that older smallholder farmers may develop good managerial skills and efficient farming practices over a long time. Significantly, and perhaps more importantly, older farmers are more likely to spend less time on off-farm activities and therefore focus more on farm activities.

Education level of household head is negative and significant at 1%. This implies that better educated famers in the sample tend to be less inefficient. This is consistent with Koirala, et al. (2015) and Matsvai, et al. (2020), in which the authors found that the farmers who attained higher level of formal education were more productive and technically efficient. This is because better educated farmers were able to make well-informed production decisions. The high efficiency scores of more educated farmers in Northern Province could be because smallholder farmers who attained some basic levels of formal education are most likely to adopt technology and experience the yield augmenting effects of education. Better educated farmers are also more likely to benefit more from extension services compared to less educated farmers. This is because education would allow them to better have access to agricultural technical services and make use of the information provided by extension service officers. Better educated farmers are also likely to understand and leverage modern technological advancement to increase their productivity and technical efficiency.

In addition to the technical inefficiency sub-model parameters discussed above, the gamma estimate is almost the same in both the translog functional form (γ= 0.9672 or 96.72%) and in the Cobb-Douglas functional form ($\gamma = 0.9613$ or 96.13%). On average, both estimates show that more than 96% of the error variance is due to inefficiency. This means that most of the variation in maize output from the frontier (by farmers in the sample) is explained by technical inefficiency. The coefficient estimates of sigma-squared (σ^2) is equally almost the same in both the translog functional form (σ^2=3.382) and the Cobb-Douglas functional form (σ^2=3.307).

4.4 Specification Tests

4.4.1 Cobb-Douglas Versus Translog Functional forms

To compare which model best fitted the data between the Cobb-Douglas and the translog functional form, the Generalized Likelihood Ratio (LR) test was employed as in Conradie (2019). After computing the test statistics, the author compared them to the critical values of the mixed chi-square distribution (Kodde and Palm, 1986). The generalized likelihood ratio test is computed as:

$$\text{LR} = -2[LLH_{restricted} - LLH_{unrestricted}]$$

where $LLH_{restricted}$ and $LLH_{unrestricted}$ are values of the Log Likelihood for the Cobb-Douglas model and the translog frontier model, respectively. The Log Likelihood statistic follows a mixed chi-square (χ^2) distribution with degree of freedom equal to the number of restrictions between the Cobb-Douglas model and the one produced by the translog model (Conradie, 2019; Kodde and Palm, 1986). The restricted model is nested within the unrestricted model.

Results show that the log-likelihood ratio for the restricted (OLS) and unrestricted models are -534.34 and -509.47, respectively (see table 4 above). The calculated likelihood ratio statistic is 49.74. The chi-square critical value is 17.67 (based on ten degrees of freedom). Since the critical value (17.67) is less than the likelihood ratio statistic of 49.74, the null hypothesis that Cobb Douglas is adequate is rejected and therefore the translog model is the preferred functional form.

4.4.2 Mean Response Model Versus Frontier

With the translog functional form selected (based on the Generalized Likelihood Ratio test) as a preferred model, the Likelihood Ratio (LR) test of the one-sided error was conducted to determine whether the translog was a mean response (OLS) model or a frontier. The test statistic value of 178.25 was greater than the critical value (CV) of 10.37. Therefore, the mean response (OLS) model was rejected, and it was concluded that the model was a frontier.

4.5 Farm Household Efficiency Estimates

The estimated mean technical efficiency score stands at 0.67 or 67%, thereby revealing that, on average, the smallholder farmers included in the sample are capable of attaining only 67% of their potential output from the given set of production inputs. This finding highlights a considerable level of technical inefficiency, amounting to 33%, among the smallholder farmers in the sample. The average technical efficiency of 67% implies that smallholder farmers in Northern Province, Zambia, possess the potential to enhance their productivity by 33% through the more efficient utilization of existing technologies and resources.

Table 6:Technical efficiency of the studied farmers

TE Range	Frequency	Percentage (%)	Cumulative (%)
0.00-0.09	7	1.10	1.10
0.10-0.90	13	2.05	3.15
0.20-0.29	21	3.31	6.47
0.30-0.39	32	5.05	11.51
0.40-0.49	45	7.10	18.61
0.50-0.59	48	7.57	26.18
0.60-0.69	97	15.30	41.48
0.70-0.79	161	25.39	66.88
0.80-0.89	199	31.39	98.26
0.90-1.00	11	1.74	100.00
Min	0.02		
Max	0.93		
Mean	0.67		
S.D	0.01		
No. of observation	634		

Table 6 presents the descriptive statistics, including the minimum, maximum, mean, standard deviation, frequency, and respective percentages, of the estimated farm household efficiency. The results reveal that the average technical efficiency of maize small-scale farmers is noteworthy. The efficiency estimates for the sample encompass a broad spectrum, ranging from as low as 1 percent to as high as 93 percent, with a mean of 0.67 or 67 percent. This indicates that, on average, smallholder maize farmers in the sample can only capture approximately 67 percent of the potential output given the available inputs. Moreover, a significant majority (66.88 percent) of the farmers in the sample operate at an efficiency level below 0.80, while only 33.12 percent of the farmers exhibit a technical efficiency greater than 0.79.

4.7 Chapter Summary

This chapter presented the findings of the study. It commenced by providing an overview of agriculture in Northern Province, Zambia, along with descriptive characteristics of farm households. The results showcase the estimated parameters of the production function and the technical efficiency sub-model for smallholder maize farmers in the region. The inputs employed to establish the production frontier encompass the total land cultivated, total labor days, total kilograms of seed utilized, and total kilograms of fertilizer employed per farm. Notably, all of these input variables demonstrate statistical significance and exhibit the anticipated signs in both the Cobb-Douglas and translog models. This indicates that both models exhibit desirable behaviour.

With regard to the inefficiency variables, as anticipated, access to credit, extension services, the farmer input support program, distance between the homestead and farm, gender of the household head, age of the household head, and level of education of the household head were all observed to enhance the technical efficiency of smallholder farmers in the sample.

Chapter 5: Conclusion and Recommendations

This chapter presents a summary of the findings in relation to the study objectives, along with policy recommendations and insights for future research.

5.1 Summary and Conclusions of the Study

The agricultural sector assumes paramount importance in the Zambian economy, serving as a cornerstone of national development. However, the persistently low productivity levels, primarily among smallholder farmers, pose a significant cause for concern. This worrisome trend becomes even more critical considering that a substantial portion of the population depends on agriculture for employment and their overall livelihood.

This study aimed to assess the determinants of technical efficiency among smallholder maize producers in Northern Province, Zambia. The selection of this province was based on its agricultural potential and its predominantly rural population. The inclusion of multiple crops in addition to maize facilitated a comprehensive analysis of the entire agricultural system, with a specific focus on maize production. The analysis involved a sample of 634 smallholder farm households, selected from an initial pool of 791 households after accounting for missing observations.

The study revealed a mean technical efficiency of 67.02% among the sampled smallholder maize farmers in the Northern Province, indicating a substantial degree of inefficiency in their operations. Notably, land under cultivation emerged as the most influential production factor, followed closely by the use of fertilizers. Furthermore, the inefficiency sub-model identified several socio-economic factors that significantly influenced technical efficiency. These factors included access to credit, access to extension services, participation in farmer input support programs, distance between the homestead and farm, gender of the household head, age of the household head, and level of education of the household head.

In addition, this study provides valuable insights into the determinants of technical efficiency among smallholder maize producers in Northern Province, Zambia. The findings underscore the critical role of effective land management and appropriate fertilizer usage in enhancing efficiency. Moreover, the study highlights the importance of socio-economic factors, such as access to credit and extension services, as well as the household head's characteristics and educational attainment, in improving technical efficiency. These findings have implications for policymakers and stakeholders seeking to promote agricultural productivity and sustainable development in the region.

Based on these findings, it can be inferred that the agricultural production in the Northern Province can be enhanced through policies aimed at facilitating smallholder farmers' access to production credit, extension services, and maximizing their benefits from the farmer input support program. Consequently, the introduction of a new comprehensive agriculture support program by the United Party for National Development government of Zambia, as outlined in both the 2022 and 2023 national budgets by the Ministry of Finance, holds tremendous potential for significantly improving the productivity of smallholder farmers.

5.2 Policy Recommendations of the Findings

Considering the significance of agriculture to the Zambian economy and in light of the findings of this study, the following recommendations have been identified to enhance the productivity and technical efficiency of smallholder farmers in Northern Province:

1. The government should encourage the uptake of credit through promoting and strengthening rural savings groups such as village banking to facilitate access to credit to support agricultural activities. By taking part in these savings groups, members can get small production loans. Importantly, farmers with good loan repayment records could further have access to loans from other finance institutions such as microfinance institutions.

2. The government should prioritise the recruitment of additional extension officers to ensure widespread access to extension services. Current statistics reveal an alarming ratio of only one extension officer for every 1,000 smallholder farmers, indicating an urgent need for improvement. Furthermore, the scarcity of extension workers is worsened by the lack of efficient transportation options, as most officers rely on bicycles, which presents challenges in reaching remote areas promptly. To tackle these issues, the government should consider allocating a higher budget to these services.

3. The government should endeavour to enhance the extent and/or adoption of the input support program. If the challenge primarily stems from insufficient funding, the government could allocate a portion of the Constituency Development Fund (CDF) towards bolstering input support. The CDF serves as a funding source for rural development, which can encompass localized agricultural advancements. Addressing the matter of appropriate targeting necessitates comprehensive monitoring and evaluation measures.

4. In addition to the aforementioned strategies, the government could explore the involvement of smallholder farmers themselves in assessing the effectiveness of the input support program. By actively engaging beneficiaries, they can contribute to identifying potential gaps and offering need-based recommendations. Furthermore, it is crucial to ensure the provision of high-quality inputs, as research indicates that farmers who utilized improved seeds and fertilizers exhibited greater productivity levels (Mason et al., 2018). To achieve this, it is imperative to bolster the regulations governing input supply, thereby minimizing discrepancies between farmers' expectations and the actual inputs they receive.

5.3 Recommendations for further Research

1. The findings of this study deviate significantly from those of Ng'ombe (2017), whose study also examined the Northern Provinces. In contrast to our study, Ng'ombe (2017) discovered that labor and nine out of ten variables in the inefficiency sub-model were not statistically significant. This disparity could be attributed to the fact that the author considered an excessive number of variables for a sample size as large as 791. Another possible explanation is that Ng'ombe (2017) utilized data from 2001, 2004, and 2008, whereas there have been numerous developments in the agriculture sector since then. To address these limitations, future research could employ more recent data and replicate our study in other provinces. Nonetheless, caution should be exercised in future studies employing the translog functional form to ensure that an excessive number of variables is not included, especially when dealing with relatively small sample sizes, as this could potentially distort the results.

2. Further research should consider a comparative analysis of smallholder famers in all the districts in Northern Province to determine possible differences in productivity and technical efficiencies. This could potentially help policy makers decide on how to distribute productions credit, extension services and agricultural support programme.

3. Future research should examine the impact of crop diversification on the efficiency of smallholder maize farmers in Northern Province, Zambia. This is important because these farmers grow multiple crops and own multiple fields, but the current study couldn't explore this due to data unavailability. Investigating this relationship would provide valuable insights into the technical efficiency of smallholder maize farming.

References

Abate, G., Rashid, S., Borzaga, C., Getnet, K., 2016. Rural finance and agricultural technology adoption in Ethiopia: Does the institutional design of lending organizations matter? *World* Development, 84(1): 235-253.

Achandi, E.L., 2018. Technical efficiency: A study of smallholder rice farmers in Kilombero district, Tanzania. *Journal of Economic Bibliography, 5(3):10-16*

Aigner, D., Lovell, C.K., Schmidt, P., 1977. Formulation and estimation of stochastic frontier production function models. *Journal of Econometrics. 6(1): 21-37*.

Battese, G.E. and Corra, G.S.,1977. Estimation of a Production Frontier Model: With Application to the Pastoral Zone off Eastern Australia. *Australian Journal of Agricultural Economics*, 21(3):169-179.

Battese, G.E and Coelli, T.J., 1988. Prediction of firm-level technical efficiencies with a generalized frontier production function and panel data. *Journal of Econometrics*. 38(3):387-399.

Battese, G.E and Coelli, T.J., 1992. Frontier Production Functions, Technical Efficiency and Panel Data: With Application to Paddy Farmers in India. *Journal of Productivity Analysis*. 3(1):153-169.

Battese, G.E, Coelli, T. and Rao, D.S., 1995. A model for technical inefficiency effects in a stochastic frontier production function for panel data. *Empirical Economics 20(2): 325-332*

Bravo-Ureta, B.E., Solis, D., Lopez, V.H.M., Maripani, J.F., Thiam, A., Rivas, Teodoro., 2007. Technical efficiency in farming: a meta-regression analysis. *Journal of Productivity Analysis*, 27(1): 57-72

Charnes, A., Cooper, W.W., Rhodes, E., 1978. Measuring the efficiency of decision-making units. *European Journal of Operational Research*, 2(6): 429-444.

Chiona, S., Kalinda, T and Tembo, G., 2014. Stochastic frontier analysis of the technical efficiency of smallholder farmers in central province, Zambia. *Journal of Agricultural Science* 6(10): 108-118

Coelli, T. J., Rao, D. P., O'Donnell, C. J. & Battese, G. E., 2005. An Introduction to Efficiency and Productivity Analysis. 2nd ed. New York: Springer.

Conradie B., 2019. Designing for successful land reform for the extensive grazing sector. *South African Journal of Agricultural Extension,* 47(2):1-12

Constantin, P., Martin, L., Rivera, E., 2009. Cobb-Douglas, Translog Stochastic Production Function and Data Envelopment Analysis in total factor productivity in Brazilian Agri-business. *Journal of Operations and Supply Chain Management*, 2(2): 20-34

Chapoto, A., Jayne, T.S., 2006. Effects of maize marketing and trade policy on price unpredictability in Zambia. Working Paper No. 38. Lusaka: Food Security Research Project.

Conradie, B., Galloway, C. and Renner, A., 2022. Private extension delivers productivity growth in pasture-based dairy farming in the Eastern Cape, 2012–2018. *Agrekon*, 61(2), pp.109-120.

Conradie, B. and Genis, A., 2020. Efficiency of a mixed farming system in a marginal winter rainfall area of the Overberg, South Africa, with implications for thinking about sustainability. *Agrekon*, 59(4), pp.387-400.

Conradie, B., Piesse, J. and Stephens, J., 2019. The changing environment: Efficiency, vulnerability, and changes in land use in the South African Karoo, 2012–2014. *Environmental Development*, 32, p.100453.

CSO, MAL and IAPRI, 2016. Rural Agricultural Livelihood Survey: 2015 Survey Report, Lusaka: IAPRI.

Dessale, M., 2019. Analysis of technical efficiency of small holder wheat-growing farmers of Jamma district, Ethiopia. *Agriculture and Food Security*, 8(1). https://doi.org/10.1186/s40066-018-0250-9

Dube, L. and Guveya, E., 2014. Technical Efficiency of Smallholder Out-grower Tea (Camellia Sinensis) Farming in Chipinge District of Zimbabwe. *Greener Journal of Agricultural Science*. 4(1): 368-377. 10.15580/GJAS.2014.8.091114354).

Dube, L. and Mugwagwa, K. E., 2017. Technical efficiency of smallholder tobacco farmers under contract farming in Makoni District of Manicaland Province, Zimbabwe: A Stochastic Frontier Analysis. *Scholars Journal of Agriculture and Veterinary Sciences*, 4(2): 68-78.

Duffy, J., Papageorgiou, C., 2000. A cross-country empirical investigation of the aggregate production function specification. *Journal of Economic Growth*, 5(1): 87-120

Farrell, M.J., 1957. The Measurement of Production Efficiency. *J. Royal Statistical Society*. Series A (General), 120 (3): 253-281.

Fletschner, D., 2008. Women access to credit: Does it matter for household efficiency? *American Journal of Agricultural Economics*, 90(3): 669-683

Girabi, F., Mwakaje, A.G., 2013. The impact of microfinance on smallholder farm productivity in Tanzania: The case of Iramba district. *Asian Economic and Financial Review*, 3(1): 227-242.

Greene, W.H., 1980. Maximum likelihood estimation of econometric frontier functions. *Journal of Econometrics*, 13(1): 27-56.

Ahmadzai, Hayatullah., (2017). Crop Diversification and Technical Efficiency in Afghanistan: Stochastic Frontier Analysis. 10.13140/RG.2.2.17959.14244/1.

Headey, D., Alauddin, M., Rao Prasada, D.S., 2010. Explaining agricultural productivity growth: an international perspective. *Agricultural Economics*, 41(1): 1-14.

Howard, J. and Mungoma, C., 1996. Zambia’s Stop-And-Go Revolution: The Impact of Policies and Organizations on the Development and Spread of Maize Technology. *Food Security International Development Policy Syntheses* 11274, Michgan State University

Janzen, S., Carter, M., 2019. After the drought: The impact of microinsurance on consumption smoothing and asset protection. *American Journal of Agricultural Economics*, 101(3): 651-671.

Jondrow, J., Lovell, C.K., Materov, I., Schmidt, P., 1982. On the estimation of technical inefficiency in the stochastic frontier production function model. *Journal of Econometrics*, 19 (2-3): 233-238.

Karmiloff, I., 1990. "Zambia". In Manufacturing Africa: Performance and Prospects of Seven Countries in Sub-Saharan Africa. London: James Currey.

Kodde, D.A. and Palm, F.C.,1986.Wald Criteria for Jointly Testing Equality and Inequality Restrictions. *Econometrica*, 54, 1243-1248.

Kneller, R., Stevens, P.A., 2003. The specification of the aggregate production function in the presence of inefficiency. *Economics Letters*, 81(2): 223-226.

Koirala, K., Mishra, A., Sitienei, I., 2015. Farm productivity and technical efficiency of rural Malawian households: Does Gender Make a Difference? Retrieved from https://ageconsearch.umn.edu/record/196903

Koricho, M.G., Ahmed, M.H., 2021. The impact of credit on the technical efficiency of food crop producing smallholder farmers in Ethiopia. Agricultural Financial Review, Vol. ahead of print No. ahead of print. https://doi.org/10.1108/AFR-08-2021-0108

Kumbhakar, S., Lovell, C., 2000. Stochastic Frontier Analysis. Cambridge: Cambridge University Press. DOI: 10.1017/CB09781139174411

Kumbhakar, S., Tsionas, E., 2006. Estimation of stochastic frontier production functions with input-oriented technical efficiency. *Journal of Econometrics*, 133(1): 71-96.

Kumbhakar, S., Wang, H.J., 2015. A practitioner's guide to stochastic frontier analysis using Stata. Cambridge University Press, New York, NY.

Kydd, J., 1988. Coffee after Copper? Structural Adjustment, Liberalisation, and Agriculture in Zambia. *The Journal of Modern African Studies*, 26(2): 227-251.

Khandker, S., Koolwal, G., 2014. Does Institutional Finance Matter for Agriculture? Evidence Using Panel Data from Uganda. Policy Research Working Paper; No. 6942. World Bank, Washington, DC.

Lee, L.F., 1983. A test for distributional assumptions for the stochastic frontier functions. *Journal of Econometrics*, 22(3): 245-267.

Mango, N., Makate, C., Mlambo, B.H., Siziba, S., Lundy, M., 2015. A stochastic frontier analysis of technical efficiency in smallholder maize production in Zimbabwe: The post-fast-track land reform outlook. *Cogent Economics and Finance*, 3(1): DOI: 10.1080/23322039.2015.1117189

Mariyono, J., 2019. Microcredit and technology adoption: Sustained pathways to improve farmers' prosperity in Indonesia. *Agricultural Finance Review*, 79(1):85-106.

Mason, N.M., Jayne, T.S., 2013. Fertiliser subsidies and smallholder commercial fertilizer purchases: Crowding out, leakage and policy implications for Zambia. *Journal of Agricultural Economics*, 64(3): 558-582

Mason, N.M., Jane, T.S., Mukuka, R.M., 2013. Zambia's Input Subsidy Programmes. *Agricultural Economics*, 44(6): 613-628

Mason, N.M., Kuteya, A., Ngoma, H., 2018. Recent innovations to Zambia's farmer input support programme and insight on short-run effects. International Conference of Agricultural Economists, Vancouver, Canada. Accessed [Online] at : https://www.canr.msu.edu/fsp/outreach/presentations/Zambia%20FISP%20innovations%20&%20prelim%20results%20on%20short-run%20effects%20-%20ICAE%20-%202018_07_30%20-%20final%20-%20web%20-%20Nicole%20Mason.pdf

Masunda, S. and Chiweshe, A. R., 2015. A stochastic frontier analysis on farm level technical efficiency in Zimbabwe: A case of Marirangwe smallholder dairy farmers. *Journal of Development and Agricultural Economics*, 7(6):237-242.

Matsvai, S., Mushunje, A., Tatsvarei., 2022. Technical efficiency impact of microfinance on small-scale resettled sugar cane farmers in Zimbabwe. *Cogent Economics and Finance*, 10(1): DOI:10.1080/23322039.2021.2017599

Meeusen, W. and van Den Broeck, J., 1977. Efficiency Estimation from Cobb-Douglas Production Functions with Composed Error. *International Economic Review*, 18(2): 435-444. DOI: http://dx.doi.org/10.2307/2525757

Melkani, A., Mason, N.M., Mather, D.L., Chisanga, B., 2019. Smallholder maize market participation and choice of marketing channel in the presence of liquidity constraints: Evidence from Zambia. Feed the Future Innovation Lab for Food Security Policy Research Briefs No. 303623, Michigan State University. DOI: 10.22004/ag.econ.303623

Miller, E., 2008. An assessment of Constant Elasticity of Substitution and Cobb-Douglas Production Function. Congress Budget Office. Available [Online]: https://econpapers.repec.org/paper/cbowpaper/19992.htm

Ministry of Agriculture and Cooperatives, Central Statistics Office, and Food Security Project., 2008. Patterns of Maize Farming Behaviour and Performance among Small and Medium Scale Smallholder in Zambia. MACO, CSO, FSP: Lusaka.

Ministry of Finance (MoF)., 2021. Zambia: 2022 National Budget Address. Minister of Finance. Lusaka

Ministry of Finance (MoF)., 2022. Zambia: 2023 National Budget Address. Minister of Finance. Lusaka

Musaba, E. and Bwacha, I., 2014. Technical efficiency of small-scale maize production in Masaiti District, Zambia: A stochastic Frontier Analysis Approach. *Journal of Economics and Sustainable Development*, 5(4):104-111

Mukwalikuli, M., 2018. Determinants of technical efficiency of smallholder farming in Lukulu, Zambia. *World Journal of Research and Review* (WJRR), 6(4): 60-65

Mwanamwenge, M. and Harris, J., 2017. Sustainable Diets for All: Agriculture, Food Systems, Diets and Nutrition. Discussion paper, Lusaka: Hivos

Nelson, V., 2000. Rural Transport Policy Toolkit: Livelihoods profile for Northern and Luapula Provinces. Natural Resources Institute, University of Greenwich.

Neubert, S., Komm, M., Krumsiek, A., Schulte, A., Tatge, N., Zeppenfeld, L., 2011. Agricultural development in a changing climate in Zambia: Increasing resilience to climate change and economic shocks in crop production. Studies, No. 57, ISBN 978-3-88985-493-3.

Ng'ombe, J.N. and Kalinda, T., 2015. A stochastic analysis of technical efficiency of maize production under minimum tillage in Zambia. *Sustainable Agriculture Research*, 4(2):31

Ng'ombe, J.N., 2017. Technical Efficiency of smallholder maize production in Zambia: a stochastic meta-frontier approach. *Agrekon*, 56(4): 347-365

Okoye, B.C., Abass, A., Bachwenkizi, B., Asumugha, G., Alenkhe, B., Ranaivoson, R., Randrianarivelo, R., Rabemanantsoa, N., Ralimanana, I., 2016. Differentials in technical efficiency among smallholder cassava farmers in Central Madagascar: A Cobb-Douglas stochastic frontier production approach. *Cogent Economics and Finance*, 4(1): 1143345, DOI: 10.1080/23322039.2016.1143345

Piesse, J., Conradie, B., Thirtle, C. and Vink, N., 2018. Efficiency in wine grape production: comparing long-established and newly developed regions of South Africa. *Agricultural Economics*, 49(2), pp.203-212.

Pottier, J., 1988. Migrants no more: Settlement and survival in Mambwe villages, Zambia. Bloomington: Indiana University Press.

Prasanna, R., Lakmali, N., 2016. Estimating technical efficiency among smallholder potato producers in Welimada, Sri Lanka. *Sri Lanka Journal of Economic Research*, 4(1): 59-74.

Rana, Z., Bapari, Y., 2018. Credit availability and technical efficiency of boro rice in Pabna District, Bangladesh: A stochastic frontier analysis. *International Journal of Sustainable Development*, 4(1): 08-16

Saasa, O.S., 1994. Policy reforms and structural adjustment in Zambia: The Case of Agriculture and trade. Technical Paper No. 35, AFRI/SD and REDSO/SA, Washington.

Seshamani, V., 1992. The Economic Policies of Zambia in the 1980s: Towards Structural Transformation with a Human Focus. The Macmillan Press Limited: London Incornia, G.A., Van der Hoeven, R and Mkandawire, T. 1992.

Siegel, P.B., Alwang, J., 2005. Poverty Reducing Potential of Smallholder Agriculture in Zambia: Opportunities and Constraints. African Region Working Paper Series No. 85. The World Bank, Washington, DC.

Taylor, K.T., Banda-Thole, C., 2013. Tourism development potential of the Northern Province of Zambia. American Journal of Tourism Management, 1(1A): 10-25.

Tchale, H., Sauer, J., 2007. The efficiency of maize farming in Malawi. A Bootstrapped Translog Frontier. *Cahiers d'Economie et Sociologie Rurales*. 82-83. DOI:10.3406/reae.2007.2044

The Norwegian Centre for International Agricultural Development (NORAGRIC) and the International Union for the Conservation of Nature and Natural Resources (IUCN), 1989. Environmental Effects of Agricultural Change and Development in The Northern Province, Zambia, Viken: Norwegian University of Life Sciences.

Thurlow, J. and Wobst, P., 2006. Not all growth is equally good for the poor: the case of Zambia. *Journal of African Economics: 15 (4), 603-625*.

Udry, C., 1994. "Gender, Agricultural production and the Theory of the Household." *Journal of Political Economy, 104(5):1010-1046.*

United Nations Office for the Coordination of Humanitarian Affairs (OCHA), 2021. Emergency Plan of Action (EPoA) Zambia: Food Insecurity. Available [Online] at: https://reliefweb.int/report/zambia/zambia-food-insecurity-emergency-plan-action-epoa-dref-operation-n-mmdrzm014.

Wadud, A., White, B., 2000. Farm household efficiency in Bangladesh: a comparison of stochastic frontier and DEA methods. *Applied Economics*, 32(13): 1665-1673

World Food Programme (WFP), 2020. Zambia Annual Country Report 2020. Country Strategic Plan 2019-2014. Available [Online] at: https://docs.wfp.org/api/documents/WFP-0000125456/download/

White, H., Leavy, J. and Seshamani, V., 2005. Agriculture Development in Zambia's Northern Province: Perspectives from the field level. IDS Bulletin, 36(2): 132-138.

World Bank, 2021. Zambia's Farmer Input Support Programme and Recommendations for Re-designing the Programme. Agriculture for Development. World Bank, Washington, DC.

World Bank, 1994. Zambia Poverty Assessment. Vol. 1. Main Report (No. 12985-ZA). Human Resources Division, Southern African Development, Africa Regional Office.

Wulf, J., 1988. Zambia under the IMF Regime. *African Affairs* 87(349): 579-594

Appendix

Appendix 1: Questionnaire (Source: IAPRI, 2015)

SECTION 1: DEMOGRAPHIC CHARACTERISTICS OF HOUSEHOLD MEMBERS

Tell us about each adult member of the household born in or before 2000 (12 years and above) who lived in this household between May 2013 and April 2014. If this household is part of a polygamous family, ask only about the household members at this household.

1.1 List all the members of this household (List the household-head' first and then all adult members born in or before 2000 who lived in this household since the beginning of May 2014).

Member	Name	In which year was …… born?	What is the sex of .... ? 1=male 2=female	What is The marital status of …...?	What is the highest level of formal education .... completed? (See codes below)	How many labor days did each adult member contribute to this household's farm in the 2013/14 growing season? (1=none at all → go to next member; 2=less than 20 days; 3=more than 20 days)
1						
2						
3						
4						
5						
6						
7						
8						
9						
10						

Education Levels								
00	None		06	Standard 5 (Grade 6)		13	Form 6 (Lower)
01	Sub-standard A (Grade 1)		07	Standard 6 (Grade 7)		14	Form 6 (Upper)
01	Sub-standard B (Grade 1)		08	Form 1 (Grade 1)		15	College student
02	Standard 1 (Grade 2)		09	Form 2 (Grade 9)		16	Undergraduate student
03	Standard 2 (Grade 3)		10	Form 3 (Grade 10)		17	Certificate/Diploma
04	Standard 3 (Grade 4)		11	Form 4 (Grade 11)		18	Bachelor's degree
05	Standard 4 (Grade 5)		12	Form 5 (Grade 12)		19	Master's degree & above

SECTION 2: FARMLAND AND USE

2.1. Tell the respondent that we would like to know about the household farmland and use during the 2014/2015 agricultural season.

Field ID	What is the total area of this field? (Unit 1=lima; 2=acre; 3=hectare; 4=square Metre)	What portion of the area was planted? (Unit=Hectares)	What main crop or use did the hh put this field to this agricultural season (2014/15)? (See Codes below)	What quantity of basal dressing fertiliser did the household	What quantity of top-dressing fertiliser did the household	How much of this crop did the hh harvest from this field? (Unit=Kgs)

					apply? (Unit=Kgs)	apply? (Unit=Kgs)	
1							
2							
3							
4							
5							
6							

Crop codes							
1	Maize		8	Soya beans		15	Cowpeas
2	Sorghum		9	Seed cotton		16	Sugarcane
3	Rice		10	Irish potatoes		17	Popcorn
4	Millet		11	Virginia tobacco		18	Coffee
5	Sunflower		12	Burley tobacco		19	Cassava
6	Groundnuts		13	Mixed beans		20	Paprika
7	Velvet beans		14	Bambara nuts		21	Other' crop (specify)

2.2 What is the distance in kilometres of this field from the homestead?

SECTION 3 – ACQUISITION OF SEED AND/OR PLANTING MATERIAL

3.1. Did you receive any maize seed or fertiliser through farmer input support programme (FISP)? (1=yes, 0=No)

SECTION 4: RURAL LOANS/CREDIT

We now want to ask about any loans/credit the household may have acquired to support agricultural production and the household's access to loans/credit.

4.1. Did any member of your household borrow money or obtain a loan/credit (cash or in-kind) from any of the sources below to support agricultural production during the 2013/14 agricultural season? (1=yes, 0=No)

1	Government-run programme
2	Commercial bank
3	ZNFU Lima Credit Scheme
4	Farmers' union or cooperative (excluding ZNFU Lima Credit Scheme)
5	Micro credit institution / community credit scheme
6	Out-grower scheme
7	Input credit from private company (excluding outgrower schemes)
8	NGO / faith-based organization / church
9	Friend/relative/informal moneylender (e.g., kaloba)
10	Company leasing equipment to own (e.g., Rent to Own)
11	Community-based savings group (e.g., SILC, VSLA, etc.)
12	Other (specify)

SECTION 5: QUESTIONS ABOUT AGRICULTURAL INFORMATION

Please tell us about the advice/information the household received from government extension officers, organizations, private agents or individual farmers.

5.1. Has any member of the household ever received any advice on the following services? (1 = Yes; 2 = No →go to next type of activity/advice).

1	Zero tillage (excluding chitemene)?
2	Minimum tillage using planting basins (potholes)?
3	Minimum tillage using ripping?
4	Leaving crop residues in the field and incorporating it into the soil?
5	Using crop residues as mulch (cut and spread on field)?
6	Rotating cereals with legumes/nitrogen-fixing crops?

7	Intercropping cereals with legumes/nitrogen-fixing crops?
8	Applying animal manure?
9	Applying plant manure/green manure or compost?
10	Applying lime?
11	Leaving land fallow to rest the soil?
12	Growing crops that are well suited to soil and weather conditions in your area?
13	Agroforestry (Use of trees to protect/improve your crop or crop yields)
14	Information about the problems associated with aflatoxin in maize and/or groundnuts?
15	Use of chemical grain protectants (e.g., Actellic chirinda matura dust) to protect maize in storage from weevils?

Appendix 2: Data Consent Form

IAPRI

IAPRI Data Sharing Consent Form

I ..Elijah Mumba.................................. a student at..University of Cape Town............and student ID number..MMBELI004...............pursuing a bachelors/Masters/PhD in ..Development Economics.... ....do hereby solemnly commit to abide by the stipulated conditions for accessing the Rural Agricultural Livelihood Survey dataset for the years 2012 and 2015. The conditions set out are as follows:

1) I commit to NOT share the said dataset with ANY individual or institution under any circumstances whatsoever without express permission from IAPRI.
2) I further commit to contribute to the body of knowledge through publication of a working paper under IAPRI as a condition for accessing the RALS 2015 dataset.

IAPRI reserves the right to share only relevant sections of the data or aggregated variables based on the submitted research proposal. Data will not be released if the research proposal is similar to on-ongoing research by the institution.

Signature:.. Name: Elijah Mumba..

Date: 24/02/2022.. Place: Kabulonga..

Expected date for submission of Working paper:..30/12/2022..

Data shared on 21/04/2022 by Mitelo Subakanya

IAPRI Data Policy: All prior rounds of the IAPRI/MSU/FSRP/CSO Supplemental Panel Surveys to the 1999/00 Post Harvest Survey (2001, 2004, and 2008) are available upon request through IAPRI Research Director, Dr. Antony Chapoto. The Rural, Agriculture, and Livelihoods 2012 Survey (RALS12) is now publicly available since August 1, 2015 and can be accessed by contacting Dr. Chapoto as stated above. RALS15 dataset will be publicly available starting August 30, 2018.