# Determinants and Change in Total Factor Productivity of Smallholder Maize Production in Southern Zambia

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**Abstract**

Smallholder maize production in Zambia has been characterized by low productivity despite concerted efforts at improving the situation as is evident in budgetary allocations to programmes such as the Farmer Input Support Programme (FISP). The study assessed if there was a change in total factor productivity (TFP) in smallholder maize production in Southern Province of Zambia between the 2010/11 and 2013/14 agricultural seasons. Using a balanced panel of 778 smallholder farmers, a Stochastic Frontier Analysis was used to estimate the Malmquist Productivity Index (MPI) in measuring the productivity change in maize production. The change in TFP was further decomposed into its components, efficiency change (EC) and technical change (TC) so as to understand more on the change in productivity. It was found that over the period of study, the mean EC was 0.8734, implying that technical efficiency (TE) had declined by 12.7 % with the mean TFP of 0.9401, indicating that over the study period TFP had fallen by 5.99 %. The results further showed that the age of the farmer, education of the farmer, household size, membership to a farmer organization, ownership of cattle, access to credit, and drought stress were significant ($\rho<0.05$) factors in explaining TFP. In light of the findings, some recommendations were made for policy including the need to facilitate farmers' access to credit, sensitize farmers on the benefits of belonging to farmer organizations, on ownership of livestock such as cattle and for massive investment in irrigation infrastructure.

**Keywords:** total factor productivity, efficiency change, technical change, Malmquist Productivity Index, smallholder maize farmers, Southern Zambia

## 1. Introduction

Agriculture is one of the most important sectors for most developing countries when it comes to poverty alleviation. This stems from the fact that in most developing countries, the majority of the poor are engaged in agriculture and so growth in the sector is often associated with relatively large reduction in poverty (Timmer, 2005). In Zambia, the agricultural sector contributes 13 to 20% of the Gross Domestic Product (GDP) and also accounts for about 70% of the total labour force (CSO, 2012). However, poverty reduction efforts are hampered by low producitivity in the sector especially that of maize. There is need for studies that give an understanding on how productivity [as measured through total factor productivity (TFP)] evolves over time along with its determinants to gain insights on how to improve the sector.

Maize is by far the most widely grown crop in Zambia as it is the country's staple and principal food security crop. The over 1.1 million smallholder farmers grow most (80%) of the maize despite being resource poor (Tembo and Sitko, 2013). Apart from being the major source of household food security in Zambia, maize accounts for 41% of the value of farm income including the value of production and sales (Jayne et al., 2010).

Over the past several decades, improving productivity in maize production has been one of the major goals of the Zambian government (Xu et al., 2009). For instance, in its recognition of the need to improve productivity in maize production as well as to assure national food security and increased incomes to various stakeholders, government introduced the Fertilizer Support Programme (FSP) in 2002. In 2009, FSP was renamed and reformed as the Farmer Input Support Programme [FISP] (Jayne et al., 2010). One of the implicit aims of the programme has been that with the majority of resource poor small-scale farmers accessing subsidized inputs, the adoption of improved maize seed and fertilizer would increase and in turn, result in increased productivity. Besides their benefits in addressing the problem of soil degradation, Conservation Agriculture (CA) practices are being promoted and advocated for by both government and non-governmental organizations (NGOs) because they are also associated with efficient use of resources and improved productivity (Jayne et al., 2010).

The national maize yield average of 2.2 tons/ha is, however, extremely low as compared to that of other countries in the sub-Saharan African (SSA) region. Most of the small-scale producers are very far from realizing the potential maize yield of 5 tons/ha for open pollinated varieties and 10 tons/ha for hybrids (MACO et al., 2008).Given that other inputs such as fertilizer are not accounted for in the computation of yield as a measure of productivity, there is every reason to believe that that productivity (2.2 tons/ha) could even be lower if all resources used in maize production are considered. There is still potential for increased maize yields of smallholder producers in Zambia to match those of other countries in SSA. In fact, South Africa's maize yields are reported to be about twice as high as Zambia's (Tembo and Sitko, 2013).

To sustain increased food production, an insight into all possible sources of agricultural production growth is required. An understanding of TFP change in smallholder maize production and its decomposition into various components could be the key in boosting agricultural productivity growth in maize. In Zambia, for most crops including maize, the productivity indicators often employed are Partial Factor Productivity (PFP) measures, such as yield (output per unit area of land). When used to measure increase in production that results from improved productivity, a PFP measure such as yield could be misleading. This is partly because changes in yield do not correlate as well with changes in production as TFP measures do (see Benin, 2016). Conversely, a TFP measure, such as the Malmquist Productivity Index (MPI), is amenable to decomposition into finer indicators like efficiency change (EC) and technical change (TC) (Coelli et al., 2005; Ogundele and Okoruwa, 2014; Benin, 2016). Since TFP measures lend themselves to decomposition into component indices, more insight into possible drivers of TFP itself could be grasped (Benin, 2016).

Studies on productivity and production of maize have been conducted in Zambia (Kimhi, 2003; Zulu et al., 2007; Jayne et al., 2010; Chiona, 2011; Chiona et al., 2014; Ng'ombe, 2017). Most of these studies have used cross-sectional data which have inherent limitations, including the inability to control for unobserved heterogeneity across study units. This could be a potential source of bias in estimates (Hill et al., 2011). However, with panel data that is not the case (Hsiao, 2003; Baltagi, 2005). Moreover, as Baltagi (2005) points out, besides giving more data points on the study units, panel data can better model TE, and indeed, EC, than cross-sectional data. This study therefore contributes to the existing literature by using panel data to assess TFP change and its determinants in smallholder maize production in Southern Province of Zambia.

The rest of the paper is organized as follows; Section 2 looks at the methodology. Results and discussions are presented in Section 3 and then Section 4 gives the conclusion and policy implications.

## 2. Methodology

### *2.1 Measuring TFP Change, EC and TC*

Literature points to various techniques used in measuring TFP change. The Tornqvist Index and the MPI are among the prominent indices used for measuring TFP change. With the Tornqvist Index, TFP change can be measured but it cannot be decomposed into its various components as the index is premised on the assumption that production is always on the frontier (Fare et al., 1994). However, with the MPI, and assuming the existence of inefficiencies in production, it is possible to measure TFP change that is attributable to both EC and TC. The MPI is simply the relative measure of the ratio of the observed output to the maximum output possible in one period $(t+1)$, to the ratio of the observed output to the corresponding maximum output possible in another period $(t)$, given the vector of inputs in the respective periods (Coelli et al., 2005). Aside from making it possible to measure TFP change without data on input and output prices, the MPI allows for the decomposition of the TFP change into its various components such as EC and TC (Coelli et al., 2005; Headey et al., 2010; Benin, 2016). These features of the MPI especially make it more attractive as an index for measuring TFP change over other techniques such as the Tornqvist Index in situations where data constraints and sometimes non-availability or unreliability of data on input and output prices could possibly pose challenges. Moreover, with the MPI, it is unnecessary to make behavioural assumptions such as cost minimization or profit maximization (Coelli et al., 2005).

In the present study, the output-oriented MPI was used to measure TFP change and its components. Besides their application in the definition of various index numbers, distance functions provide the conceptual basis for describing technology in such a way as to facilitate the measurement of efficiency and productivity. With distance functions, a multi-input, multi-output production technology can be described without necessarily specifying the behavioural objective of firms (see Coelli et al., 2005). In order to specify MPI using output distance functions, the existing technology has to be defined. It may be useful to regard a general distance function as being evaluated relative to the frontier of the 'true', but unknown underlying technology.

Where the technology is defined as

$$D(x,y) = \inf\{\theta : (y/\theta, x) \in T\} \tag{1}$$

Where the technology is defined as $T = \{(x, y): x\ can\ produce\ y\}$ and $y \in R_{+}^{M}$ is the vector of outputs, and $x \in R_{+}^{M}$ is the vector of inputs. Since the ultimate goal is measuring change in productivity, time has to be incorporated too. Based on the definition by Caves et al. (1982), Fare et al. (1994), and Coelli et al.(2005), the MPI can be expressed as follows:

$$M^{t} = \frac{D_o^t(x^{t+1}, y^{t+1})}{D_o^t(x^t, y^t)} \tag{2}$$

with period $t$ as the reference technology. Similarly, MPI can be defined based on period $t+1$ technology as:

$$M^{t+1} = \frac{D_o^{t+1}(x^{t+1}, y^{t+1})}{D_o^{t+1}(x^t, y^t)} \tag{3}$$

Equation (2) and Equation (3) show that the estimation of the MPI between any two periods depends on the choice of the technology employed. To avoid the effect of an arbitrarily chosen reference technology, we have to change between the two data points relative to a common technology (Caves et al., 1982; Coelli et al., 2005). Thus, the MPI is defined as the geometric mean of two indices based on period $t$ and $t+1$ technologies as shown in Equation (4):

$$M_o(x^{t+1}, y^{t+1}, x^t, y^t) = \left[\left(\frac{D_o^t(x^{t+1}, y^{t+1})}{D_o^t(x^t, y^t)}\right)\left(\frac{D_o^{t+1}(x^{t+1}, y^{t+1})}{D_o^{t+1}(x^t, y^t)}\right)\right]^{\frac{1}{2}} \tag{4}$$

Given observed quantities of inputs and outputs, the value of $M_o$ can be computed. Computed values of $M_o > 1$, $M_o < 1$ and $M_o = 1$, indicate that between periods $t$ and period $t+1$, TFP increased, decreased and remained constant, respectively. Equation (5) gives an equivalent way of expressing Equation (4).

$$M_o(x^{t+1}, y^{t+1}, x^t, y^t) = \frac{D_o^{t+1}(x^{t+1}, y^{t+1})}{D_o^t(x^t, y^t)}\left[\left(\frac{D_o^t(x^{t+1}, y^{t+1})}{D_o^{t+1}(x^{t+1}, y^{t+1})}\right)\left(\frac{D_o^t(x^t, y^t)}{D_o^{t+1}(x^t, y^t)}\right)\right]^{\frac{1}{2}} \tag{5}$$

In Equation (5), the ratio outside the brackets measures the change in the output-oriented Farrell (1957) technical efficiency (TE) between period $t$ and period $t+1$. The geometric mean of the two ratios inside the brackets captures the shift in technology between the two periods as evaluated at $x^t$ and $x^{t+1}$, that is, TC.

*2.2 Conceptual Framework*

In the present study, TFP meant the measure of productivity that accounts for all the inputs used in the production process. For a typical smallholder maize farmer in Zambia, the conventional inputs used are maize seed, land, fertilizer and labour. While some farmers might use all these inputs in producing maize, others might not apply fertilizer for some reasons such as financial constraints. Similarly, some farmers might use low yielding local or recycled maize seed instead of the recommended high yielding varieties [HYV] (improved seed varieties) due to financial constraints or even unavailability of HYV seed on the market. An increase in TFP over time means increased productivity. This in turn implies increased maize production without increased levels of inputs. Some literature refer to TFP as a measure of Solow residual growth because it measures that part of output growth not accounted for by changes in conventional factors of production or inputs (Headey et al., 2010; Benin et al., 2015). However, since it implicitly assumes that all producers operate on the frontier, the Solow residual growth is as a result of technological change[1] only, that is, farmers adopting better techniques of producing maize (see Fare et al., 1994; Headey et al., 2010). In this study, it has been assumed that not all the farmers produce on the frontier, thus allowing for inefficiencies; and so increased maize production can potentially come from improved TE over time.

The study followed Farrell (1957) definition of technical efficiency as the ratio of the observed output to the maximum potential output possible given the existing technology. Thus, in this study by EC is meant the change of technical efficiency over time. Over time, a farmer's TE could improve (movement towards the frontier), deteriorate (movement away from the frontier) or stay constant.

In the study, TFP[2] was defined as the ratio of the maize output to the aggregate of all inputs used in producing the maize by any particular smallholder farmer.

As shown in Figure 1, TFP can change as result of EC and/or TC. Thus, socio-economic and institutional factors that affect EC and/or TC could ultimately affect TFP. Thus, policy makers can make use of this to raise TFP and so bring about increased maize production and growth in the long run, without necessarily increasing resources. Figure 1 further shows that increased production of maize is also possible through increased use of resources such as area of land. However, compared to increased maize production that results from a rise in TFP, that which is from increased use of resources is unsustainable.

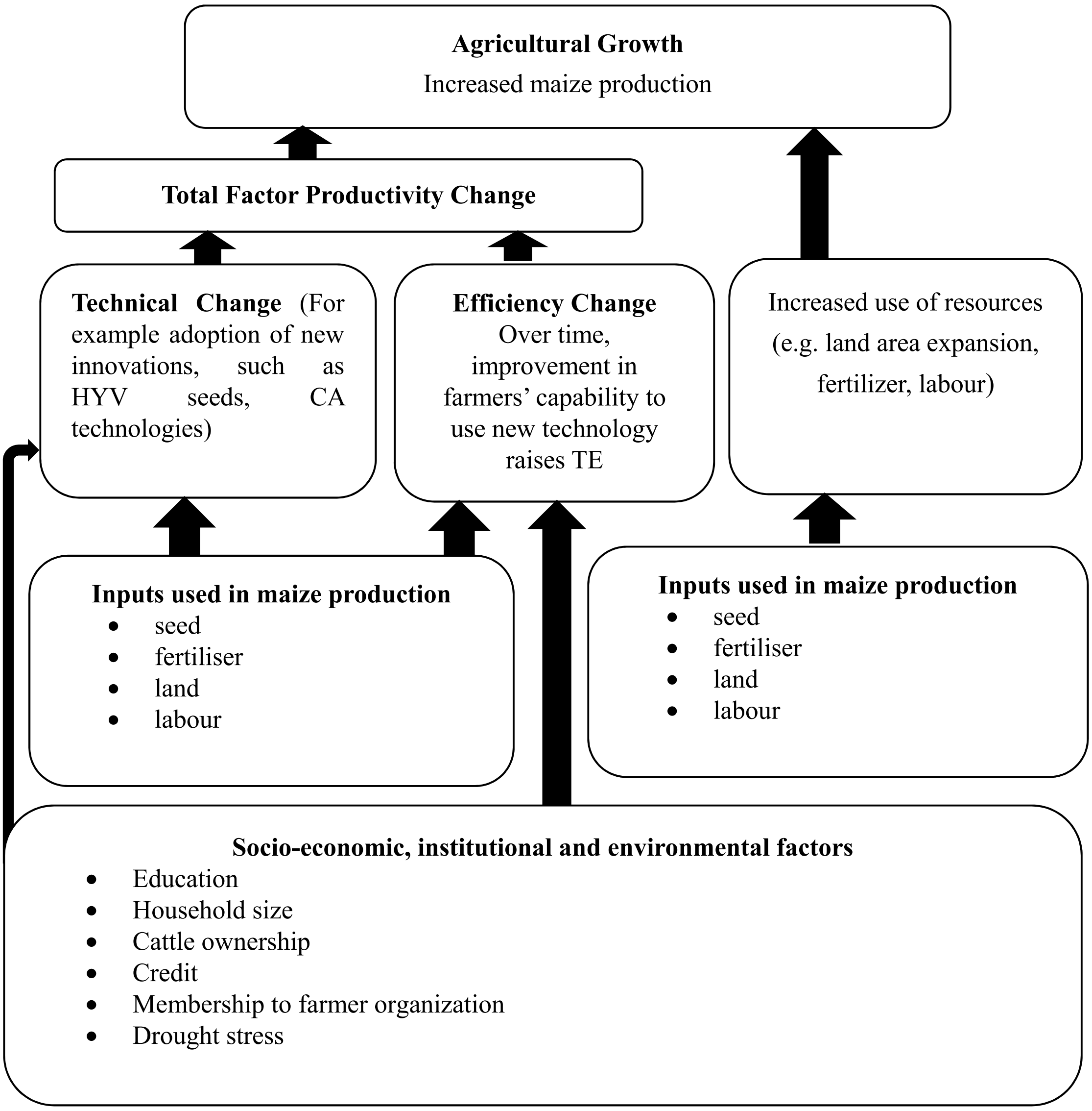


Figure 1. Possible relationships among various variable affecting TFP

*Source: Authors*

As already pointed out, it should be expected that any factors that affect either EC or TC will ultimately affect TFP. Thus, the determinants of TFP may vary. To the extent that the age, years of education of a farmer, household size can affect TE, so they will be expected to ultimately affect TFP.

*2.3 Data Analysis*

2.3.1 Stochastic Frontier Analysis

The translog production function was used to estimate the output distance functions. According to Battese (1992), the stochastic production function for panel data can be expressed as $y_{it} = f(x_{it}\,; \beta) exp(v_{it} - u_{it})$

$$i = 1,2, \dots, N \text{ and } t = 1,2, \dots, T \qquad (6)$$

Where $y_{it}$ is the output of the $i^{th}$ farm in the $t^{th}$ time period; $x_{it}$ is a vector of inputs used in the production process, $\beta$ is a vector of parameters to be estimated; $v_{it}$ are the error terms assumed to be identically and independently distributed (iid) and follow a normal distribution, $N(0,\sigma_v^2)$. The $v_{it}$ are also assumed to be uncorrelated with the regressors. The $u_{it}$ are the technical inefficiencies. To allow for time-varying technical inefficiency, the following model, the following model, as proposed by Battese and Coelli (1992) was adapted:

$$u_{it} = exp[\eta(t-T)]u_i \tag{7}$$

Where $\eta$ is the parameter to be estimated. For values of $\eta > 0$, $\eta < 0$ and $\eta = 0$ the implication is that TE improves, deteriorates, and is invariant, respectively, over time. The $t$ is the $t^{th}$ period of production; $T$ is the terminal period of production, $u_i$ are the non-negative random variables associated with technical inefficiencies of production and assumed to be iid with a mean of 0 and a variance $\sigma_u^2$ that is, $u_i \sim iidN^+(0,\sigma_u^2)$. In short, in the study, the $u_i$ were assumed to follow a half-normal distribution, as opposed to the commonly used truncated-normal distribution. According to Battese (1992), the most widely used assumption of the truncated-normal form of $u_i$ is more appropriate in cases where it is believed that the technical inefficiencies among firms are relatively high. Compared with other crops, maize is the most widely grown crop by the majority smallholder farmers and with which many farmers are most familiar. Hence, the assumption of half-normally distributed inefficiency effects was considered plausible in the study. A notable shortcoming of the model in Equation (2) is that technical efficiency is only allowed to vary monotonically over time, that is, simply knowing the rank ordering of two or more farmers in one period means that one could tell their rank ordering in subsequent periods (Kwon and Lee, 2004; Coelli et al., 2005). There are other models that can allow for non-monotonic variation in technical efficiencies among firms as suggested by other authors (Kumbhakar, 1990). However, as Kwon and Lee (2004) point out, besides entailing the estimation of many parameters, some of these more general and flexible models have not been estimated empirically. Given that the present study used panel data spanning a relatively short period of time (2010/11 and 2013/14 seasons), it was plausible to adapt the inefficiency model given by Equation (2).

The parameter, $\gamma$, measures the proportion of the composite error term in Equation (6) which is due to farmers' inefficiencies. The parameter $\gamma$ can be expressed as:

$$\gamma = \frac{\sigma_u^2}{(\sigma_u^2 + \sigma_v^2)} \tag{8}$$

From Equation (8), it follows that $\gamma$ must lie between zero and 1 inclusive. If $\gamma = 0$, this implies the non-existence of technical inefficiencies, whereas if $\gamma = 1$ implies the non-existence of random noise. To calculate an index of TFP between period $t$ (the base period) and period $t+1$ (the present period), EC and TC have to be measured. Following Coelli et al. (2005), the technical efficiency of production for the $i^{th}$ firm at the $t^{th}$ year can be measured using Equation (9) as:

$$TE_{it} = E\left[\exp(-u_{it})/(\mathrm{v}_{it} - u_{it})\right] \tag{9}$$

The change in technical efficiency for the $i^{th}$ firm (*EC*) is calculated as:

$$EC_{it} = \frac{TE_{it+1}}{TE_{it}} \tag{10}$$

Where $TE_{i,t+1} = D_0^{t+1}(x^{t+1}, y^{t+1})$ and $TE_{it} = D_0^t(x^t, y^t)$ are the technical efficiencies of the $i^{th}$ firm calculated using the period $t+1$ and period $t$ output distance functions, respectively. Similarly, the TC index between the periods $t$ and $t+1$ for the $i^{th}$ firm can be calculated from the estimated parameters of the stochastic production frontier model. Technical change can be calculated as the geometric mean of the technical change magnitudes (TCMs) for the periods $t$ and $t+1$ for any individual farm (Fuentes et al., 2001; Coelli et al., 2005).

$$TCM(x_{it}, y_{it}) = \exp\left\{-\left[\theta_t + \theta_{tt}(t+\frac{1}{2}) + \sum_{k=1}^{K}\omega_k \ln x_k^{it}\right]\right\} \tag{11}$$[3]

The TFP index can then be obtained as the product of the EC and TC indices, that is, $TFP_{it} = EC_{it} \times TC_{it}$. The TFP indices thus generated were regressed on the determinants of total factor productivity as posited by literature and empirical studies (Alam et al., 2011) as in Equation (12).

$$lnTFP_{it} = x_{it}\varphi + \varepsilon_{it} \tag{12}$$

Where TFP, as already stated, is total factor productivity; $x_{it}$ is a vector of socio-economic, institutional and environmental factors that explain change in TFP; $\varphi$ is a vector of parameters to be estimated and $\varepsilon_{it}$ are the stochastic error terms assumed to be $\sim iidN(0, \sigma^2)$.

*2.4 The Empirical Model*

To obtain the parametric decomposition of TFP, a functional form of the production function has to be specified. The parameter estimates thus obtained are then used in assembling the components of TFP, namely, EC and TC (Headey et al., 2010). For the best results, the functional form has to be flexible and relatively easy to compute. The translog functional form adequately meets the aforementioned properties. Thus, the present study adopted the translog production function as it has been extensively used in frontier studies (Fuentes et al., 2001; Kwon and Lee, 2004). In particular, the study adapted the translog model employed by Kwon and Lee (2004) as follows:

$$\begin{aligned} ln(Output_{it}) = {} & \alpha_0 + \alpha_1 ln(Land_{it}) + \alpha_2 ln(Seed_{it}) + \alpha_3 ln(Fert_{it}) + \alpha_4 ln(Lab_{it}) + \theta_t t + \tfrac{1}{2}\delta_{11}[ln(Land_{it})]^2 \\ & + \tfrac{1}{2}\delta_{22}[ln(Seed_{it})]^2 + \tfrac{1}{2}\delta_{33}[ln(Fert_{it})]^2 + \tfrac{1}{2}\delta_{44}[ln(Lab_{it})]^2 + \tfrac{1}{2}\theta_{tt}t^2 \\ & + \beta_{12} ln(Land_{it}) ln(Seed_{it}) + \beta_{14} ln(Land_{it}) ln(Lab_{it}) + \omega_1 ln(Land_{it})t \\ & + \beta_{23} ln(Seed_{it}) ln(Fert_{it}) + \beta_{24} ln(Seed_{it}) ln(Lab_{it}) + \omega_2 ln(Seed_{it})t \\ & + \beta_{34} ln(Fert_{it}) ln(Lab_{it}) + \omega_3 ln(Fert_{it})t + \omega_4 ln(Lab_{it})t \end{aligned} \quad (13)$$

Whether $Output_{it}$ are the kilogrammes (kg) of maize harvested by the $i^{th}$ farmer in the $t^{th}$ period; Similarly, $Land_{it}$ , $Seed_{it}$, $Fert_{it}$, $Lab_{it}$, are, respectively, the hectares (ha) of land used, the kg of seed planted, the kg of fertilizer, and the man-days of labour used by the $i^{th}$ farmer in the $t^{th}$ period; $t$ is the period varying from $1 = (2010/11)$ to $2 = (2013/14)$; $\alpha_i$, $\forall_i = 0, \ldots, 4$; $\forall_i = 1, \ldots, 4$; $\theta_i, \theta_{tt}; \beta_{ij}, \forall_i = 1, \ldots, 3$ and $\forall_j = 2, \ldots, 4$; and $\omega_i, \forall_i = 1, \ldots, 4$ are the parameters to be estimated; $v_{it}$ is the idiosyncratic error term of the $i^{th}$ farmer in the $t^{th}$ period; $u_{it}$ is the technical inefficiency of the $i^{th}$ farmer in the $t^{th}$ period. Furthermore, as stated earlier, $v_{it} \sim iidN(0, \sigma_v^2)$.

Then employing equations (2), (4), (5) and (6), TE, EC, and TC were calculated. In particular, the TEs for the two seasons (2010/11 and 2013/14) were determined in FRONTIER 4.1 Software and Excel was then used to compute the EC indices using Equation (10). Using data for the 2010/11 and the 2013/14 seasons, TCM for each of the two seasons was calculated. The TC was calculated as the geometric mean of the TCMs thus obtained. Then using Excel, the EC and TC indices were multiplied to obtain the TFP indices.

*2.5 Determinants of TFP*

The Pooled Ordinary Least Squares (POLS) was used to model the determinants of TFP. Using $TFP_{it} = EC_{it} \times TC_{it}$, the index of productivity $(TFP_{it})$ was regressed on the determinants of productivity as posited by theory and empirical literature. For this purpose, STATA was used. For easy interpretation, the log-lin specification was used as follows:

$$\begin{aligned} \ln(\mathrm{TFP_{it}}) = {} & \varphi_0 + \varphi_1 \mathrm{age_{it}} + \varphi_2 \mathrm{educ_{it}} + \varphi_3 \mathrm{hhsize_{it}} + \varphi_4 \mathrm{plotsize_{it}} + \varphi_5 \mathrm{plotsize_{it}^2} + \varphi_6 \mathrm{farmgrp_{it}} + \\ & \varphi_7 \mathrm{credit_{it}} + \varphi_8 \mathrm{cattle_{it}} + \varphi_9 \mathrm{ox-drawn\_plough_{it}} + \varphi_{10} \mathrm{drought_{it}} + \varepsilon_{it} \end{aligned} \quad (14)$$

Where $ln(TFP_{it})$ is the logarithm of the TFP index for the $i^{th}$ farmer in the $t^{th}$ period; $\varphi_i$ are the parameters to be estimated while $\varepsilon_{it}$ are the idiosyncratic error terms assumed to be $\sim iidN(0, \sigma^2)$. And tests were made to determine the specification of the production function as well as the structure of production and the sources of productivity change.

*2.5.1 Likelihood Ratio Tests*

The likelihood ratio (LR) test is used for testing which of two given specifications; one as specified by the null hypothesis, or another as specified by the alternative hypothesis, is the appropriate. The likelihood ratio test is given in Equation (15).

$$LR = -2\{lnL_R - lnL_U\} \quad (15)$$

Where LR is the likelihood ratio statistic to be computed; $lnL_R$ and $lnL_U$ are the values of the log-likelihood functions for the restricted and unrestricted models, respectively. The test statistic follows a Chi-square $(x^2)$ distribution. If the value of the LR-test statistic is greater than the critical value at the $\alpha$-level of significance, the null hypothesis in favour of the restricted model is rejected (Hill et al., 2011). By employing the LR-test, the following null hypotheses were tested on the model specification and structure of production as well as the sources of productivity change (Alam et al., 2011).

$H_0: \beta_{lm} = \delta_{nn} = \omega_k = 0$; the Cobb-Douglas functional form, as opposed to the translog functional form better fits the production data.

$H_0: \gamma = 0$; there are no inefficiencies among smallholder maize farmers in Southern Province.

$H_0: \mu = 0$; the inefficiency term follows a half-normal distribution.

$H_0: \omega_k = \theta_t = 0$; this null hypothesis postulates the non-existence of technical change.

### *2.6 Data Sources and Study Area*

The study was done in the Southern Province, one of the leading producers of maize in Zambia. Southern Province is covered by both the agro-ecological zones I and IIa, in the southern and the northern regions, respectively. Agro-ecological zone I covers the valley region which are prone to droughts and normally receive annual rainfall of below 800 mm. Agro-ecological zone IIa covers the plateau area and receives rainfall amounts of between 800 and 1,000 mm per year (Chapoto et al., 2016). The province has a population of 1,589,926 with the majority (85%) being rural. It has a farmer population of over 180,000 making up about 11.3% of the total population of the province (CSO, 2012). For many years, Southern Province has been the leading producer and bread-basket of maize in Zambia. However, in recent years it has been alternating the top position with Central and Eastern Province.

#### 2.6.1 Sources of Data

The study used secondary data to come up with a panel dataset between the 2010/11 and the 2013/14 agricultural seasons. The data were collected through the Rural Agricultural Livelihoods Surveys (RALS) administered by the Indaba Agricultural Policy Research Institute (IAPRI) in collaboration with the Central Statistical Office (CSO) and the Ministry of Agriculture and Livestock (MAL). The first and second waves of the survey were conducted in 2012 and 2015, respectively. The survey attempted as much as possible to track the same sample of rural households in all the 10 provinces nationwide so as to ensure a statistically valid and comprehensive means of assessing trends in various variables. Using probability proportional to the size of the sampling scheme, the RALS drew a sample of 442 Standard Enumeration Areas (SEAs). The size of the SEA was dependent on the number of households located within that SEA on the sampling frame in accordance with the Zambia 2010 Census of Population. All the households in each sample SEA were listed and each household was categorised into 3 groups based on a specific formula. A random number of 20 households were then selected. In cases where the 3 categories had adequate numbers of households (10 or more) listed, the distribution of the sample households was such that Category C was allocated 10 households, Category B, 5 households and Category A, 5 households.

For this particular study, a balanced panel dataset of 778 farm households was used. It is noteworthy that the data set originally had 966 farm households as at the first wave in 2012. However, due to attrition on the follow-up survey of 2015 for reasons including refusal to respond, non-contact, shifting from the SEA and dissolution of some households, the sample size reduced to 778 households.

## 3. Results and Discussions

### *3.1 Descriptive Statistics*

Table 1 gives some descriptive statistics for the variables used in the analysis. The mean age of the household head was about 48 years with a range of 20 to 100 years.

On average, the household head had spent 6.6 years in formal education, implying that most of the farmers had been up to primary school. The average household size was 7.4 persons. This household size incorporated all household members including children less than 12 years of age. However, in the analysis, only members of the farm family household who were at least 12 years old were included to proxy household size for the labour endowment. It should be noted that only household members who were at least 12 years old would contribute towards labour used in production. The average household size for the active members was 4.2 persons.

Table 1. Descriptive statistics for the study variables

| Variable | Mean | Std. deviation | Min | Max |
|---|---|---|---|---|
| Age (years) | 47.7 | 14.44 | 20 | 100 |
| Education (years) | 6.63 | 3.62 | 0 | 18 |
| Household size (persons) | 7.40 | 3.24 | 1 | 25 |
| Plot size (ha) | 1.27 | 1.35 | 0.0000972 | 15 |
| Plot size$^2$ (ha$^2$) | 3.45 | 10.44 | 0.0000945 | 225 |
| Output (kg) | 4,520.07 | 5,546.13 | 82.5 | 35,592.50 |
| Land (ha) | 2.42 | 2.23 | 0.12 | 19.00 |
| Seed (kg) | 52.9 | 49.1 | 2.34 | 440.80 |
| Fertiliser (kg) | 347.8 | 521.9 | 0.00 | 7,600.00 |
| Labour (man-days) | 91.1 | 45.8 | 15.00 | 450.00 |
| Gender (Male=1; Female=0) | 1,289 | | | |
| | (82.84%) | | | |
| Farmer organization (Yes=1, No=0) | 935 | | | |
| | (60.09%) | | | |
| Access to credit (Yes=1, No=0) | 186 | | | |
| | (11.95%) | | | |
| Cattle ownership (Yes=1, No=0) | 892 | | | |
| | (57.33%) | | | |
| Ox-drawn plough (Yes=1, No=0) | 1,091 | | | |
| | (70.12%) | | | |
| Drought (Yes=1, No=0) | 935 | | | |
| | (15.30%) | | | |
| Observations | 1,556 | | | |

The average plot size of land harvested of maize over the period was 1.27 ha. Plot size was used to proxy farm size. Output was the quantity of maize grain harvested by the farm households in kg. The average output was 4,520.70 kg of maize, with a minimum and maximum of 82.5 and 35,592.50 kg, respectively. Incidentally, the overall variation in output was 5,546.13 kg. It is worth noting that the overall variation in output was positive implying that there might have been an increase in maize output between 2010/11 to 2013/14. This tends to tie in with the report by GRZ (2016) showing that in the period under review, national maize production had increased by about 330,291 tons. The average amount of land allocated to maize production was 2.42 ha, a statistic which supports the fact that most of the farmers were small-scale (with land holding less than 5 ha). On average, 52.2 kg of maize seed was planted over the period of study.

Table 1 further shows that, on average, the farmers applied 348 kg of fertilizer over the two agricultural seasons. The average number of man-days of labour allocated to maize production over the two seasons was 91.1 man-days/season. Table 1 also includes six (6) dummy variables on the socio-demographic, environmental and institutional factors that explain TFP. Of the total 1,556 observations over the study period, the majority farmers were male (82.8%). About 60.9% of the observations show that farmers had membership to some farmer organization. Only 11.9% of the 1,556 observations had households which accessed credit. On average, 57.3% of the 1,556 observations showed ownership of cattle. About 70% of the observations had reported ownership of an ox-drawn plough. Table 1 further shows that 15.3% of the observations had households that reported having experienced drought stress during the period under review.

### *3.2 Model Specification Tests*

Table 2 shows results of the hypothesis tests for the appropriateness of the translog distance function over the Cobb-Douglas production function. The first hypothesis concerns the appropriate functional form of the output distance function to represent the production frontier. For this purpose, the LR-test statistic of 125.95, which is greater than the critical value of 23.68, rules out the appropriateness of the Cobb-Douglas function $(H_0: \beta_{lm} = \delta_{nn} = \omega_k = 0)$ in preference to the less restrictive translog output distance function.

The second specification test was about the appropriateness of including the inefficiency error term in the model as opposed to only the standard error term, so as to have the composite error term. The null hypothesis $(H_0: \gamma = 0)$ was rejected as the LR-test statistic of 71.26 was greater than the critical value of $\chi_1^2 = 3.84$.

Table 2. Model specification tests

| Null hypothesis | LR-test | DF | Critical value | Decision | Conclusion |
|---|---|---|---|---|---|
| $H_0: \beta_{lm} = \delta_{nn} = \omega_k = 0$ | 125.95 | 14 | $x_{14}^2 = 23.68$ | Reject $H_0$ | Translog is appropriate |
| □ *k,l,m and n* | | | | | |
| $H_0: \gamma = 0$ | 71.26 | 1 | $x_1^2 = 3.84$ | Reject $H_0$ | Inefficiencies exist |
| $H_0: \mu = 0$ | 3.19 | 1 | $x_1^2 = 3.84$ | Accept $H_0$ | Inefficiencies follow a half-normal distribution |
| $H_0: \eta = 0$ | 5.80 | 1 | $x_1^2 = 3.84$ | Reject $H_0$ | Inefficiencies are time-varying |
| $H_0: \omega_k = \theta_t = 0$ | 2.39 | 4 | $x_4^2 = 9.49$ | Accept $H_0$ | No technical change |
| □ *k and t* | | | | | |

*Source: Authors' analysis using RALS data, 2012 and 2015*

The third model specification test was on the appropriateness of the distribution of the inefficiency error term $U_{it}$. The LR-test statistic of 3.19, which is less than the critical value of $x_1^2 = 3.84$ indicates that the null hypothesis should be rejected. Thus, the half-normal, as opposed to the truncated-normal distribution, better models the distribution of the inefficiency error component.

The fourth hypothesis test of time-invariant inefficiency effects was rejected as the LR-test statistic of 5.80 was greater than the critical value of $x_1^2 = 3.84$ as is shown in Table 2. This implies that TE was varying over the study period. This in turn means that the null hypothesis stating that there is no efficiency change in smallholder maize production between the 2010/11 and 2013/14 seasons was rejected.
The other null hypothesis, $H_0: \omega_k = \theta_t = 0$, testing whether there was TC in smallholder maize production in Southern Province over the study period could not be rejected. As is shown in Table 2, the LR-test statistic of 2.39 is less than the critical value of $x_4^2 = 9.49$, and so the null hypothesis could not be rejected.

### *3.3 Estimation Results of the Translog Distance Function*

Table 3 shows the estimated Maximum Likelihood coefficients of the stochastic translog distance function. Based on the estimates of the components of the error term, technical inefficiency is correctly specified. The value of $\gamma = 0.589$ indicates that inefficiency accounts for about 58% of the total variation in maize production, and it is significantly different from zero at the 1% level. This result corroborates the LR-test statistic of 71.26 in Table 2 and justifies the inclusion of the inefficiency error component in the composite error term of the translog production function.

Table 3. Estimation results[4] of the translog distance function

| Variables | Parameter | Coefficient | Std. error | t-value | p-value |
|---|---|---|---|---|---|
| Constant | $\alpha_0$ | 1.277 | 2.826 | 0.45 | 0.652 |
| *ln*(*Land*) | $\alpha_1$ | -2.490*** | 1.108 | -2.25 | 0.021 |
| ln(*Seed*) | $\alpha_2$ | 3.799*** | 1.184 | 3.21 | 0.001 |
| ln(*Fert*) | $\alpha_3$ | -0.175 | 0.108 | -1.62 | 0.110 |
| ln(*Lab*) | $\alpha_4$ | -0.317 | 0.675 | -0.47 | 0.638 |
| ln(*Land*)ln(*Seed*) | $\beta_{12}$ | 0.730*** | 0.273 | 2.67 | 0.008 |
| ln(*Land*)ln(*Fert*) | $\beta_{13}$ | -0.0462 | 0.0286 | -1.62 | 0.110 |
| ln(*Land*)ln(*Lab*) | $\beta_{14}$ | 0.1004 | 0.160 | 0.63 | 0.501 |
| ln(*Seed*)ln(*Fert*) | $\beta_{23}$ | -0.0095 | 0.0298 | -0.32 | 0.741 |
| ln(*Seed*)ln(*Lab*) | $\beta_{24}$ | -0.0828 | 0.166 | -0.49 | 0.632 |
| ln(*Fert*)ln(*Lab*) | $\beta_{34}$ | -0.00565 | 0.0149 | -0.38 | 0.701 |
| 0.5(ln*Land*)$^2$ | $\delta_{11}$ | -0.5416** | 0.269 | -2.01 | 0.045 |
| 0.5(ln*Seed*)$^2$ | $\delta_{22}$ | -0.889*** | 0.316 | -2.81 | 0.005 |
| 0.5(ln*Fert*)$^2$ | $\delta_{33}$ | 0.132*** | 0.0123 | 10.73 | 0.000 |
| 0.5(lnLab)$^2$ | $\delta_{44}$ | 0.1194 | 0.1193 | 1.00 | 0.290 |
| ln(*Land*)*t* | $\omega_1$ | 0.0108 | 0.152 | 0.07 | 0.951 |
| ln(*Seed*)*t* | $\omega_2$ | -0.0259 | 0.156 | -0.17 | 0.869 |
| ln(*Fert*)*t* | $\omega_3$ | -0.0129 | 0.0132 | -0.98 | 0.334 |
| ln(*Lab*)*t* | $\omega_4$ | 0.079 | 0.0684 | 1.15 | 0.245 |
| *t* | $\theta_t$ | -0.279 | 0.547 | -0.51 | 0.615 |
| Gamma | $\gamma$ | 0.589*** | 0.0448 | 13.15 | 0.000 |
| Sigma-squared | $\sigma^2$ | 0.819*** | 0.0742 | 11.04 | 0.000 |
| Eta | $\eta$ | -0.341** | 0.145 | -2.35 | 0.019 |
| Likelihood function | $llf$ | -1,582.67 | | | |
| LR-test of the one sided error | | 71.26 | | | |

*Note:* *** Significant at 1% level; **Significant at 5% level; *Significant at 10% level

Table 3 also gives a value of $\eta$ = -0.341 which is statistically significant at the 5% level. The statistically significant value of $\eta$ denotes the presence of time-varying inefficiency effects in the model, while the negative sign indicates the deterioration of inefficiency over time. In other words, this implies that in the period under review, technical efficiency was decreasing over time, a result which is later confirmed by the calculated EC index.

The results show that there is a significant negative relationship between maize output and land. This negative relationship seems strange. However, the explanation could be that with most of the farmers having access to the plentiful customary land, the average farmer just uses more land than is required for the optimal levels in maize production. Additionally, they could not have enough of the other resources, especially fertilizer with which to produce the maize. Since the interaction terms in a translog function do not have any economic meaning they were not interpreted (Okoruwa et al., 2009).

**Elasticity of maize production**

Of particular importance in any production process is the knowledge regarding the responsiveness of output to inputs used, that is, the elasticity of production. In this study, the various elasticities of maize production with respect to the inputs were calculated at the sample means. Using this method, the elasticities of maize production using a translog functional form are a function of coefficient estimates and the mean values for logs of inputs (Coelli et al., 2005; Greene, 2008; Alam et al., 2011).As shown in Table 4, the maize output elasticity with respect to seed, fertilizer, land and labour are 0.53, 0.25, 0.13, and 0.01, respectively. The four production elasticities sum up to 0.92, implying the possibility of mild decreasing returns to scale in the production of maize. The implication is that if the smallholder farmers were to increase all the inputs by 1 %, maize output would increase by 0.92 %. This result is in contrast with the findings by Chiona et al. (2014) and Ng'ombe (2017), which show that smallholder maize production was exhibiting increasing returns to scale in their separate studies of Central Province and Zambia, respectively.

Table 4. Maize output elasticity

| Input | Maize output elasticity |
|---|---|
| Land | 0.13 |
| Seed | 0.53 |
| Fertilizer | 0.25 |
| Labour | 0.01 |

*Source: Authors' analysis using RALS data, 2012 and 2015*

Interestingly, using data for the three agricultural seasons (1999/00, 2002/03 and 2007/08), Ng'ombe (2017) found the returns to scale for Southern Province of 1.468. It is plausible that the smallholder maize industry in Southern Province had changed from exhibiting increasing returns to scale between 1999/00 and 2007/08 to decreasing returns to scale in the period between 2010/11 to 2013/14 as this study showed.

**Seed:** As Table 4 shows, the output elasticity with respect to seed was positive and the largest. This elasticity (0.53) implies that an increase in the quantity of maize seed used would result in increased maize output. For instance, holding other factors constant, if the quantity of seed were increased by 10% of the current levels, output would increase by 5.3%. It is noteworthy that the majority of the farmers in the study had used HYV improved seed (hybrid) varieties which are of higher quality. The result is consistent with those from other studies who observed a positive elasticity of maize output to seed. (Chiona et al, 2014; Ng'ombe and Kalinda, 2015).

**Fertilizer:**Fertilizer had the second largest elasticity of 0.25, implying that holding other inputs constant, a 10% increase in the quantity of fertilizer used would increase maize production by 2.5%.

**Land:**Maize output response to land was the third in magnitude. The elasticity of 0.13 implies that a 10% increase in the unit of land allocation to maize would increase maize output by 1.3%, holding other inputs constant. This result is also consistent with the findings in the study by Chiona et al. (2014)and Ogundele and Okoruwa (2014).

**Labour:**The maize elasticity with respect to labour was the smallest (0.01), implying that a 10% increase in the man-days of labour while holding other inputs constant would increase maize output by 0.1%.

*3.4 Change in Technical Efficiency, Technical Change and Total Factor Productivity*

The mean technical efficiencies for the 2010/11 and the 2013/14 seasons were 0.7032 and 0.6219, respectively. The mean technical efficiencies imply that on average, in the 2010/11 and 2013/14 seasons, the farmers output fell short of that at the frontier by 29.6% and 37.8%, respectively. Using the technical efficiency estimates for all the farmers in the two agricultural seasons, the indices for TFP, EC and TC were computed. Table5 presents the indices. As shown in Table 5, EC was measured as 0.8734. This result implies that over the 3-year period (2010/11 – 2013/14 agricultural seasons), the technical efficiency of the smallholder maize farmers had experienced a decline since the index is less than unity. This translates into a TE decline of 12.6%. This result is corroborated by the statistically significant negative value of $\eta = -0.341$ in Table 3, which indicates that TE had declined over time. Similar results of a declining technical efficiency were found by Ogundele and Okoruwa (2014), who reported a 16% decline of TE of rice production in Nigeria between 2002 and 2007.

Using the two-step stochastic meta-frontier approach, Ng'ombe (2017) also found that the mean TEs for smallholder maize production for Southern Province progressively declined from 0.4015 in 1999/00 through to 0.3615 in 2002/03 and further to 0.3428 in 2007/08.

Table 5. Mean values of the Malmquist Productivity Indices between 2010/11 and 2013/14

| Statistic | EC | TC | TFP |
|---|---|---|---|
| Mean | 0.8734 | 1.0760 | 0.9401 |
| Minimum | 0.5816 | 0.9339 | 0.6112 |
| Maximum | 0.9590 | 1.2001 | 1.1269 |
| Std. deviation | 0.0626 | 0.0466 | 0.0813 |
| % Change (Base=2010/11) | **-12.60** | **7.60** | **-5.99** |

*Source: Authors' analysis using RALS data, 2012 and 2015*

The TC index of 1.0760 was computed as the geometric men of the TCMs using data from both period 1 and period 2, that is, the 2010/11 and 2013/14 seasons. However, this technical change result is not statistically significant as the hypothesis test $H_0: \omega_k = \theta_t = 0$ could not be rejected since the LR-test statistic (2.39) was less than the critical value of $x_4^2 = 9.49$. The TFP was then computed as the product of EC and TC, giving the mean TFP of 0.9401. This means that in the period under review, the total factor productivity of maize farmers fell by 5.99% as shown in Table 5. Thus, the results showing the decline in total factor productivity implies that TFP might not have contributed to the increased maize production over the two seasons. Therefore, in light of this result, there is every reason to have room for doubt that the overall increased maize production as indicated by the overall increase in maize output in Table 1 was due to increased productivity. Rather, it is plausible to attribute it to increased use of inputs or resources. The results further imply that there was potential for the smallholder farmers to increase maize production by simply improving their technical efficiencies between the 2010/11 and 2013/14 agricultural seasons.

### *3.5 Determinants of Total Factor Productivity*

The POLS was used to model the determinants of TFP change following results of some specification tests. To begin with, after running the Fixed Effects (FE) and Random Effects (RE) models on the data, the Hausman test results were significant, and thus the FE was settled for. Table 6 shows the results of the POLS regression model for the determinants of TFP.

Diagnostic tests for multicollinearity and heteroscedasticity were conducted on the data. There was no presence of multicollinearity as the mean Variance Inflation Factor (VIF) of 1.90 which was far below the multicollinearity threshold of VIF=10. To test the poolability of the data and so determine whether or not the POLS was appropriate to model the determinants of TFP, an *F-test* (Chow Test) was conducted based on the results from the restrictive POLS and less restrictive Least Squares Dummy Variable (LSDV) models. The Chow Test statistic is not valid in the presence of heteroscedasticity, and so both the POLS and LSDV models were tested for heteroscedasticity before conducting the test (see Baltagi, 2005: Greene, 2008; Hill et al., 2011). It was found that heteroscedasticity was significant in both models.

However, since the nature of heteroscedasticity could not be identified in both cases, for the estimated results to be valid, the models were rerun using panel-robust standard errors. Panel-robust standard errors allow for temporal correlation of error terms for individual units as well as the variation of variances across individuals (Cameron and Trivedi, 2009). In particular, the null hypothesis for the Chow Test was $H_0: c_1 = c_2 = c_3 = \cdots c_{N-1} = 0$, where the $c_i$ are the individual-specific effects for $i = 1, \ldots, N$ farm households. The $c_i$ are the $N - 1$ dummy variables for the farm households. The computed Chow Test statistic of 0.83 was less than the critical *F-test* value of 1.30 and so the null hypothesis of no differences in the intercepts could not be rejected at the 5% level. This indicated that the unobserved heterogeneity (individual-specific effects) were not significantly different from zero. Therefore, the POLS was chosen over the FE model. As a way of reinforcing on this result, the Breusch-Pagan Lagrange Multiplier (LM) test to ascertain the appropriate estimator between the RE and the POLS was conducted. The LM test results were not significant implying that the RE was not the appropriate model. If the LM test is not significant, it means that the POLS is the appropriate model over both the RE and the FE model (Hill et al., 2011). Thus, the POLS estimator was used to model the determinants of TFP.

The results show a statistically significant negative relationship between TFP and the age of the household head. The older farmers are less likely to try out the latest technologies and agricultural practices which are more likely to bring about increased efficiency and TFP in the medium to long run (Alam et al., 2011). In particular, the results show that for an additional year of life for the household head, TFP declined by 0.05%, all other factors held constant.

Table 6. Determinants of total factor productivity (regression of $\ln(TFP)$ )

| Variable | Parameter | Coefficient | Robust Std. Error | p-value |
|---|---|---|---|---|
| Constant | $\varphi_0$ | -0.00166** | 0.00826 | 0.045 |
| Age of household head | $\varphi_1$ | -0.000501*** | 0.000137 | 0.000 |
| Education of household head | $\varphi_2$ | 0.000967* | 0.000558 | 0.083 |
| Household size | $\varphi_3$ | -0.00538*** | 0.000898 | 0.000 |
| Plot size | $\varphi_4$ | 0.00658*** | 0.00265 | 0.013 |
| Plot size squared | $\varphi_5$ | -0.000406 | 0.000252 | 0.107 |
| Farmer organization (Yes=1; No=0) | $\varphi_6$ | 0.0134*** | 0.00416 | 0.001 |
| Access to Credit (Yes=1; No=0) | $\varphi_7$ | 0.0107** | 0.00430 | 0.013 |
| Cattle ownership (Yes=1; No=1) | $\varphi_8$ | 0.00927** | 0.00426 | 0.030 |
| Ox-drawn plough (Yes=1; No=0) | $\varphi_9$ | 0.00755 | 0.00488 | 0.122 |
| Drought (Yes=1, No=0) | $\varphi_{10}$ | - 0.0199*** | 0.00594 | 0.001 |
| Observations | $n$ | 1,556 | | |
| R-squared | $R^2$ | 0.0784 | | |
| Variance Inflation Factor | VIF | 1.90 | | |

*Note:* *** Significant at 1% level; **Significant at 5% level; *Significant at 10% level

There was a negative relationship between TFP and household size. The results show that for a 10% increase in household size, TFP declined at the rate of 5.38% per year. This result is consistent with the findings by Ukoha et al. (2010) who also found a negative relationship between TFP and the household size of smallholder cassava farmers in Ohafia, Nigeria. One of the plausible explanations for this result could be the age dependency ratio in the family, the ratio of the total number of family members below and above some years to the household size, who might need attention from the household head and other older active members of the household.

The relationship between TFP and plot size was significant whereas that between TFP and the square of plot size was not. A 10% increase in plot size would result in a 6.58% rise in TFP. This result is consistent with the study by Bao (2014) who also found a positive relationship between TFP and plot size.

As shown in Table 6, compared to a non-member farmer, on average, a farmer with membership to an organization has a TFP change of 1.34% higher. A plausible explanation for this could be that a farmer organization offers a number of benefits to members. Besides being a vehicle through which extension messages and technologies are diffused, members of farmer cooperatives can enjoy access to subsidized inputs. For example, for a farmer to access subsidized inputs under FISP in Zambia, they have to belong to a registered farmer organization (GRZ, 2016). In his study on farmer organizations and food production in Zimbabwe, Bratton (1986), found that a higher proportion of farmers (32%) who belonged to farmer organizations had access to credit as compared to individual farmers (7%). Thus, it is expected that such farmers will generally have higher technical efficiency in maize production and technical know-how than their counterparts who do not belong to farmer organizations. It follows that the result reinforces the expectation of a relatively high TFP for members of organizations.

There was a positive relationship between TFP and access to credit. A farmer with access to credit has a TFP change which is 1.07% higher than a counterpart without access to credit. This finding is consistent with Ukoha et al. (2010) who also found a positive relationship between cassava farmers' access to credit and TFP. A similar positive relationship was found by Deininger and Olinto (2000) between TFP the amount of credit accessed by a farmer. A farmer with access to credit is able to purchase high quality inputs such as hybrid seed and chemical fertilizers needed for the production process. Credit could also be crucial in cases where farmers have cash constraints and so face challenges in accessing subsidised inputs under FISP.

The results further show a positive relationship between TFP and ownership of cattle. Compared to a farmer who does not own cattle, the TFP change for a farmer who owns cattle is 0.9% higher. Deininger and Olinto (2000) found a similar relationship between TFP and ownership of draught animals. The explanation is that cattle, especially oxen, could be used in agricultural activities such as land preparation, planting and weeding so that farmers in possession of cattle are expected to complete agricultural activities on time (Deininger and Olinto, 2000).

The results also show a significant negative relationship between TFP and drought stress. In particular, as compared to that for farm households who had a normal rainfall season, the TFP change for households who experienced drought was 1.99% lower. This result perhaps underscores the problem of overdependence on rain-fed agriculture, which is unfortunately widely common in much of SSA, and indeed, Zambia.

## 4. Conclusion and Policy Implications

The study found that between the 2010/11 and 2013/14 agricultural seasons, the EC of smallholder maize production was 0.8734, implying that TE fell by 12.6%. In between the same two seasons, TFP was found to be 0.9401, indicating a TFP decline of 5.99%. The fact that TFP declined over the two seasons implied that TFP did not contribute to smallholder maize production in southern Zambia. The results further showed that the age of the farmer, the years of education, household size, plot size, membership to some farmer organization, access to credit, ownership of cattle and drought stress were also important factors in explaining TFP. In light of these findings, a number of policy implications could be drawn.

Increased farmers' access to credit plays an important role in contributing to TFP. Farmers with access to credit can use it to buy farming inputs and so make them more productive in the long run. Thus, policy makers should put in measures to enhance farmers' accessibility to agricultural credit. In this regard, the central bank could help in increasing availability of agricultural credit by charging concessional bank rates to financial institutions which offer loans to farmers. The results have shown that membership to a farmer organization is positively related with a higher TFP. Farmers should be sensitized on the benefits of belonging to farmer organizations so that more of them join or form new cooperatives.

Policy makers should encourage projects that increase chances of farmers owning cattle. A good example is the *Heifer Project* by Heifer International–Zambia. Among other objectives, the project aims at empowering farm families with dairy cattle and oxen through cattle donations to cooperatives. The cooperatives subsequently pass on calves to the cooperative members. Such projects are likely to contribute to increased total factor productivity in maize production given that in most cases the same farmers also produce maize.

Since the results showed that drought stress had a considerable negative effect on TFP, it is imperative that policy makers consider massive investment in irrigation infrastructure. This would ensure that farmers do not solely rely on rainfall for maize production but supplement rains with irrigation in periods of drought or prolonged dry spells.

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## Notes

1. Technological change is the change in the use of production techniques or innovations over time (Fare et al., 1994; Coelli et al., 2005). In most literature on productivity, it is also called Technical Change (TC). Thus, in the present study, the two terms were used interchangeably. TC results in a shift in the production frontier over time.

2. It should be noted that since in practice it is virtually impossible to account for all possible inputs used in production, Multi-Factor Productivity (MFP) and not TFP, should be the better term to use. However, in keeping with most of the literature, TFP, will be preferred over the two as in Coelli et al. (2005).

3. This is the adapted form of the equation from Fuentes et al. (2001). This is in view of the fact that in this study we have only one output whereas in Fuentes et al. (2001) there were three outputs. Hence, the output parameter estimates do not appear in this adapted form of the TCM Equation.

4. The parameter $\theta_{tt}$ could not be estimated because the variable $t^2$ was dropped due multicollinearity.

Consequently, the estimate was not available for use in the estimation of TCM used in calculating technical change.