Technical efficiency of beef production in agricultural districts of Botswana: A Latent Class Stochastic Frontier Model Approach

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Abstract:

The study examined the production technologies and productive performance of smallholder beef production systems to determine the levels of technical inefficiency in the agricultural districts of Botswana. The analysis draws on data from 26 districts of Botswana for the period of 2006-2014 to estimate latent class stochastic frontiers in which the technological class to which the agricultural district belongs is determined within the model. To enable efficiency comparisons between agricultural districts across these technological classes, a meta-frontier that encompasses all the class frontiers is estimated. Components of efficiency drivers are embedded in this estimation to explain agricultural districts' technical inefficiency with respect to their respective class frontiers. Results show that beef production efficiency is positively associated with the rate of formal education and negatively related with an increase in proportion of exotic breeds, high mortality and low offtake rates, indicating the presence of considerable scope for animal husbandry improvement. The mean technical efficiency scores for beef production between 2006 and 2014 for agricultural districts in class one is 18 % whereas it is 13 % for agricultural districts in class two, implying high potential to improve beef production using the same level of agricultural inputs through efficiency-enhancing investments.

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1. Introduction

The livestock sector remains one of the most important sectors in the Botswana's economy, alongside the mining industry (Sigwele & Orlowski, 2015). It contributes about 57% of value added in the agricultural sector (van Engelen et al., 2013), where agriculture itself contributes for 2.4% of the value added in the general economy (World Bank, 2016). The sector plays an important role in the rural economy as source of food, income, employment and investment opportunities (van Engelen et al., 2013; Statistics Botswana, 2015). Within the livestock sector, the beef sub-sector is the only foreign exchange earner. Given the importance of the livestock sector in Botswana, agricultural policy tends to favour the livestock sector, especially the beef sub-sector at the expense of crop production (Bahta & Malope, 2014; Temoso, Villano, & Hadley, 2015a). However, most of the public funds and human resources allocated to the livestock sector are directed mainly to monitoring disease outbreaks, vaccination campaigns and implementing the traceability system (LITS)[1] (Bahta et al., 2015; Bahta & Malope, 2014). Limited funds are spent on improvement of input use, technology adoption and enhancing productive efficiency and market access of farmers (Sigwele & Orlowski, 2015). As a result, there is evidence that the productive performance of beef cattle farms in Botswana is very low and with negative consequences on income and GDP (Temoso, Hadley, & Villano, 2015b).

The slow growth in beef productivity has been attributed to different factors amongst others; biological inefficiencies (low birth rates and high mortality rates), inefficient operations of farms, slow adoption of improved breeding, and feeding technologies (Bahta & Baker, 2015; van Engelen et al., 2013; Temoso et al., 2015b). Majority (approximately 80%) of the livestock in Botswana are managed under traditional communal grazing system. Productivity is consistently lower in traditional/communal farms than on commercial farms (Temoso, Villano & Hadley, 2016). When compared to commercial livestock farms, traditional/communal production system is characterised by numerous production and marketing constraints such as low off-take rates (the ratio of livestock sold to total number purchases and home slaughtered), high transaction costs and failure to understand various markets' quality requirements (Bahta,

[1] The LITS and disease control programs are both for export markets 'access, particularly the European Union (EU) (Bahta, Baker, Malope, & Katijuongua, 2015).

Baker, Podisi, & Marobela, 2013; Statistics Botswana, 2015). Therefore, most research in Botswana emphasise that in order to improve the performance of the livestock sector there is a need to improve the productive performance of smallholder farmers (van Engelen et al., 2013; Mahabile, Lyne, & Panin, 2002).

The low beef productivity among the smallholder farmers can be interpreted as both a challenge and an opportunity to increase production (Sigwele & Orlowski, 2015). Historically, the need to close the gap between the current productivity levels and potential productivity levels in the beef industry have received a lot of attention amongst government agencies and international development agencies (e.g. World Bank, International Livestock Research Institute - ILRI, Australian Center for International Agricultural Research) (Bahta et al., 2013; van Engelen et al., 2013; Ransom, 2011). Recent attempts include: the Livestock Management and Infrastructure Development (LIMID) programme whose objectives are to, promote food security through improved productivity of cattle, small stock and Tswana chickens and to improve livestock management (MoA, 2010); and the International Livestock Research Institution (ILRI) project which attempts to identify factors affecting the productivity of smallholder livestock farmers and assess their competitiveness, understand and improve conditions for market participation and value addition (Bahta et al., 2013).

Although much effort has been devoted in recent times to improve beef productivity in Botswana, there is evidence that it continues to fall. The question that remains is why productivity continues to decline? That is, how much of productivity is driven by production technology and how much by technical efficiency? Several studies have attempted to analyse the sources of productivity in the livestock production in Botswana; however, such studies tend to either use partial measures of productivity (Abel, 1997; Behnke, 1985) and/or use measures that fail to account for production heterogeneity among the farms (Barnes, Cannon, & Macgregor, 2008; Mahabile et al., 2002). Only three studies (Bahta, 2014; Temoso et al., 2015b, 2016) have attempted to account for technological differences among the livestock production systems in Botswana. Bahta et al., (2015) applied a stochastic meta-frontier approach to a cross sectional data from three major livestock producing districts (South East, Chobe and Central). The study categorised beef farms according to farm type, namely cattle only farmers, cattle and crop farmers and mixed farms (i.e., beef, crop and small stock production). Also, Temoso et al (2015b) adopted a similar approach to a panel data from 26 agricultural districts representing all six agro-ecological regions in Botswana. Whilst, Temoso et al (2016) measured the productivity gap between traditional and commercial beef production systems. This study adopts a latent class model (LCM) that combines stochastic frontier approach (SFA) with a latent class structure to measure and compare the production technologies and productive performance amongst smallholder beef production systems in Botswana and explore some of their performance drivers. Contrary to the approach used by Bahta et al (2015) and Temoso et al (2015b), this approach does not need precise *prior* classification of farms; it clusters the farms by searching for differences in the production technology. The use of LCM SFA approach allows us to describe the beef cattle farms well by allowing for heterogeneity and defining segments in the sample which gives us an opportunity to identify different technologies that might exist in our sample.

This approach is quite important for our empirical application given that the livestock production system in Botswana operates within a complex system (Bahta & Malope, 2014). It simultaneously identifies technological differences and also measures technical efficiency which provides aspects of management that distinguish the most efficient district from the least efficient district. Thus, technical efficiency measures can deliver insights into the competitiveness of farms and their potential for increasing productivity and resource use (Abdulai & Tietje, 2007; Gaspar, Mesías, Escribano, & Pulido, 2009). Kumbhakar, Tsionas, and Sipiläinen (2009) discusses that productivity differences between production systems can arise either from technological differences (i.e., when one system can produce the same output with fewer inputs than the other) or differences in technical efficiency (differences in how far away producers are from a given production technology, which usually is represented by a production possibility frontier) or both. Therefore, accounting for the presence of different technologies may help policy makers choose the most suitable policy measures by identifying those aspects of the production process or environment which farmers and/or policy makers might target in order to improve livestock production. For example, a group of farmers might need improvement in productivity through efficiency enhancing policies (e.g., through education and extension programmes), whilst another group might require productivity improvement through technological progress (e.g., through investment in R&D) (Baráth & Fertő, 2015; O'Donnell, 2012). Thus, the results of this paper have important policy implications for improving productivity and development of livestock sector in Botswana.

Although the use of LCM SFA has been shown to be a very useful approach in some agricultural sectors, i.e., dairy farms (Alvarez & del Corral, 2010; Alvarez, del Corral, & Tauer, 2012; Orea, Perez, & Roibas, 2015) and crops (Baráth & Fertő, 2015), its application to beef cattle and small stock is limited (exception is a study by Cillero et al (2016), who evaluated the technical efficiency and technology heterogeneity of Irish beef farms). Therefore, this study aims to contribute to the existing literature by applying the methodology to the beef sector in Botswana to identify policy tools that can push the production technology outward and policy tools that can bring up some farmers to the level of the most efficient producers for a given production technology.

The remainder of this article is organised as follows. The next section describes the LCM SFA model as well as the data and empirical models used in the estimation. Section three describes results and discussions of farms' technical efficiency and productivity. Section four provides a summary of the main findings and some policy implications.

2. Methodology

In this study we use a stochastic frontier approach that incorporates a latent class model (LCM) to account for unobserved farm production heterogeneity. The LCM framework is applicable in situations where the researcher does not know which firms belong to which particular production technology or the number of different technologies that exist in the sample (Cillero et al., 2016; Mekonnen et al, 2015). This approach groups livestock production locations or agricultural districts[2] into 'classes' based on their probability of having a variety of characteristics that represent different technologies.

2.1. Latent class stochastic production frontier

Following Orea et al., (2015) and Mekonnen et al, (2015) we specify stochastic frontier LCM production function as follows:

$$y_{it} = \alpha_{|j} + x_{it}\beta_{|j} + v_{it|j} - u_{it|j}, \tag{1}$$

where i represent districts, t indicates time and j =1,…, J stands for class and assuming that agricultural districts being analysed operate under unknown finite number of different technologies underlying the sample data. The dependent variable, y_{it} is a measure of districts' output, x_{it} represent a vector of explanatory variables, $v_{it}|j$ is a noise term that follows a normal distribution with zero mean and class-specific constant variance, and $u_{it}|j$ is a class-specific one-sided error that captures agricultural districts' inefficiency (the distance between the observation and the frontier) and is assumed to follow a one-sided distribution (half-normal in this study). The two error components are assumed to be independent of each other. The likelihood function conditional on class j for agricultural district i at time t is given by:

[2] The data used for this study is a 10 year district level panel data created by aggregating each year's annual farm level survey, conducted by Botswana agricultural statistics office. Hence, the analysis is conducted at district level.

$$LF_{itj} = \frac{\Phi\left(-\lambda_{|j} * \varepsilon_{it|j} / \sigma_{|j}\right)}{\Phi} \frac{1}{\sigma_{|j}} \phi\left(\frac{\varepsilon_{it|j}}{\sigma_{|j}}\right) \tag{2}$$

Where $\varepsilon_{it|j} = y_{it} - \alpha_{|j} - x_{it}\beta_{|j}$, $\sigma_{|j} = \left(\sigma_{u|j}^2 + \sigma_{v|j}^2\right)^{1/2}$, $\lambda_{|j} = \frac{\sigma_{uj}^2}{\sigma_{vj}^2}$, ϕ and Φ represent the standard normal density and cumulative distribution function (Greene, 2005). Then, the overall contribution of agricultural district *i* to the conditional likelihood in each period is:

$$LF_{ij} = \prod_{t=1}^{T} LF_{itj} \tag{3}$$

The unconditional likelihood for district *i* is obtained as weighted sum of its likelihood function across *j* class, where the weights (P_{ij}) are the probabilities of class membership, or:

$$LF_i(\theta, \delta) = \sum_{j=1}^{J} LF_{ij}(\theta_j) * P_{ij}(\delta_j), \; 0 \le P_{ij} \le 1, \text{ and } \sum_{j=1}^{J} P_{ij} = 1 \tag{4}$$

Then, the logarithm of the overall likelihood function ($LF_i(\theta, \delta)$) can be obtained as the sum of the individual likelihood functions ($LF_{ij}(\theta_j)$), where θ_j represent the frontier specific parameters to be estimated:

$$\ln LF_i(\theta, \delta) = \sum_{n=1}^{N} \ln\left\{\sum_{j=1}^{J} LF_{ij}(\theta_j) * P_{ij}(\delta_j)\right\} \tag{5}$$

The prior class probabilities $P_{ij}(\delta_j)$ is parameterised as a multinominal logit model, to make sure that $0 \le P_{ij} \le 1$ and $\sum_j P_{ij} = 1$:

$$P_{ij}(\delta j) = \frac{\exp\left(\delta_{|i}' q_i\right)}{\sum_{j=1}^{J} \exp\left(\delta_{|i}' q_i\right)}, \; j = 1, \ldots, J, \tag{6}$$

Where q_i represent the vector of district-specific but time invariant variables that separate the districts into different classes, and $\delta_{|i}$ is the vector associated with parameters to be estimated (Mekonnen et al., 2015).

Maximising the overall likelihood function specified in equation 5 gives asymptotically efficient estimates of all parameters. It should be noted that unlike the two stage procedures discussed in the previous section, LCM allows for all the observations in the sample to be used to estimate the underlying technology for each class (Cillero et al., 2016). Each district belongs to one and only one class which implies that the probabilities of class membership in LCM merely reflect the uncertainty that researchers have about the true parameter (Orea et al., 2015).

The estimated parameters in equation (5) can be used to compute the posterior probabilities of class membership using the following expression:

$$P\left(j|i\right)=\frac{LF_{ij}\left(\theta_j\right)*P_{ij}\left(\delta_j\right)}{\sum_{j=1}^{J}LF_{ij}\left(\theta_j\right)*P_{ij}\left(\delta_j\right)} \tag{7}$$

The probability in equation (7) is then used to allocate each agricultural district to the class with higher posterior probability. As been noted by Alvarez et al (2006), equation (7) is time invariant, implying that each individual agricultural district is modelled in the same group overtime. $P\left(j|i\right)$ is the posterior probability for a given agricultural district *i* to belong to technology class *J*, and depends on prior parameters of class membership δ_j and the estimated parameters of the production function (θ, λ, α, σ). We apply information criteria AIC and BIC to our data in order to determine the number of classes. Orea and Kumbhakar (2004), Alvarez and del Corral (2010) and Mekonnen et al (2015) show that the AIC and BIC can be computed as follows:

$$SBIC(j)=-2\log LF(j)+K\log(N), \tag{8}$$

$$AIC(j)=-2\log LF(j)+2K, \tag{9}$$

where log LF (*j*) represents the log-likelihood function of the model with *j* classes, *N* is the number of observations and *K* represents the number of parameters to be estimated. Both models aim to identify goodness of fit and the ideal option is given to the one with the lowest value of statistics. After the *j* production frontiers have been defined, the technical efficiency of an agricultural district *i* in the t^{th} period with respect to class-*j* production frontier can be estimated using the following equation:

$$TE_{it}\Big|_j=\exp\left(-u_{it|j}\right)=\exp(-E(u_{it}\Big|_j+v_{it}\Big|_j) \tag{10}$$

2.2. Meta frontier estimation

One of the main objective of this study is to make efficiency comparisons across all districts in Botswana. The efficiency score estimates across classes, from equation (10), however, are not directly comparable due to either different frontiers or weights on the different frontiers. Following Mekonnen et al, (2015), this issue is tackled by estimating a meta-frontier that incorporates all the class frontiers and facilitates efficiency comparison of all the agricultural districts in all technology classes (Mekonnen et al, 2015). The stochastic meta-frontier production function uses both panel and cross sectional data to measure efficiency and technology gaps (Battese and Rao, 2002; Battese et al., 2004) and the estimates of meta-frontiers are commonly used to compare the production efficiency of different classes or groups, districts or countries (Mekonnen et al, 2015).

Following O'Donnell et al., (2008) and Mekonnen et al., (2015), a deterministic meta-frontier production function is expressed as:

$$y_{it}^{*} = \alpha^{*} + x_{it}\beta^{*} \tag{11}$$

Subject to

$$\alpha^{*} + x_{it}\beta^{*} \geq \alpha_{|j} + x_{it}\beta_{|j} \text{ for all } j=1, 2, \ldots, J. \tag{12}$$

Where y_{it}^{*} is the log of the meta-frontier output, α^{*} and β^{*} are the meta-frontier parameters to be estimated, whereas $\alpha_{|j}$ and $\beta_{|j}$ are the estimated parameters of the j^{th}-class frontier. The constraint in equation 12 ensures that the meta-frontier will not lie below the class frontiers as shown in figure 1. The parameters of the meta-frontier function can be obtained by minimizing the sum of the deviations (or the sum of squared deviations) between the meta-frontier and the individual class frontiers subject to the constraint that the meta-frontier envelopes all the class frontiers using a linear-programming method as suggested by O'Donnell et al. (2008) and Battese et al. (2004).

Thus, the efficiency of an agricultural district in class j can be measured relative to its own frontier.

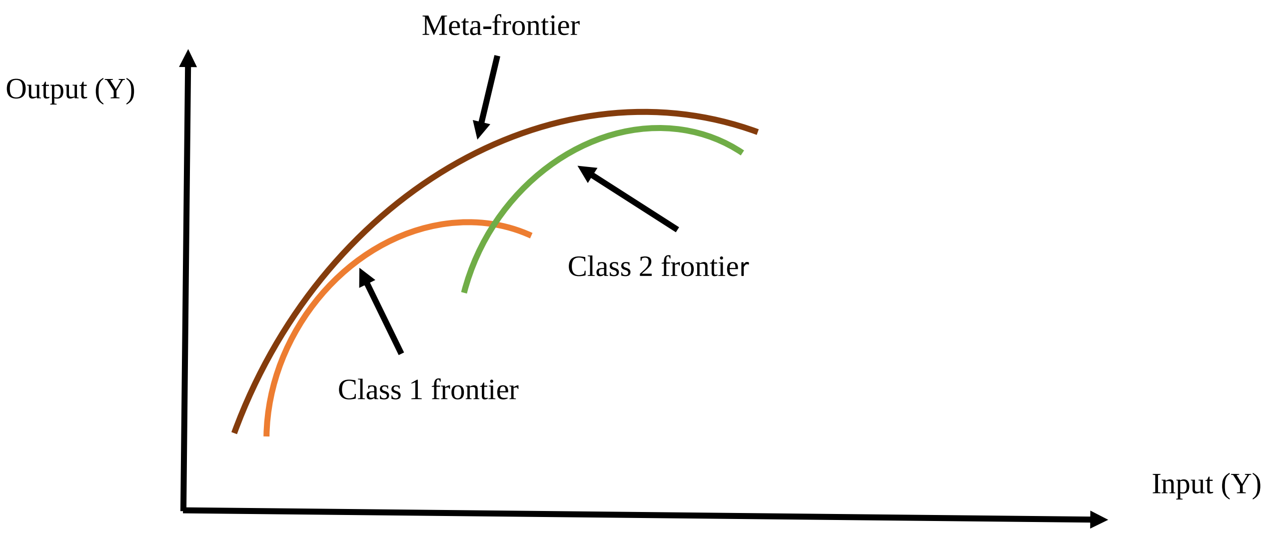

Figure 1: Graphical description of meta-frontier (Source: Adapted from Battese et al., (2004).

The closeness of each class frontier to the estimated meta-frontier, called the meta-technology ratio (MTR), is computed as a ratio of the class frontier and the meta-frontier:

$$MTR_{it}^{j} = \frac{\alpha_{|j} + x_{it}\beta_{|j}}{\alpha^{*} + x_{it}\beta^{*}} \text{ for all } j = 1, 2 \ldots J. \tag{13}$$

O'Donnell et al. (2008) and Battese et al. (2004) have shown that the technical efficiency of any country with respect to the meta-frontier can be estimated as:

$$TE_{it} = TE_{it|j} * MTR_{it}^{j} \tag{14}$$

3. Data and Empirical Model

3.1. Data and Study Area

Data for this study comes from the annual national agricultural surveys[3] of Botswana. A panel of 231 observations was constructed using the data for 26 agricultural districts of Botswana for the period of 2006–2014. The districts included are five districts of Southern region, five districts of Gaborone region, seven districts of Central region, three districts of the Francistown region, three districts of Maun region and three districts of Western region. Although the survey covers both the traditional/communal and commercial sectors of Botswana agriculture, the current study utilized only the data from traditional or subsistence farms, which holds 88% of the nation's cattle (Statistics Botswana, 2015). The Traditional or subsistence sector covers farmers operating on communal areas. The data were collected through a questionnaire administered by a team of technical assistants and cover agricultural holdings and their principal characteristics such as: characteristics of the holder and other members of the holding (age, sex, etc.), land use (crop and fallow land and measurements for such), farming implements and methods of farming, livestock counts and inventory (births, deaths, sales, home consumption, purchases), crop production by type, farming practices and enterprise, livestock water supply, farm equipment and machinery inventory.

3.2. Descriptive statistics

Table 1 shows the definition, units, and summary measures of the production function variables and variables that are used to explain technical inefficiency. The dependent variable, beef output, is the monetary value of beef output. Due to measurement difficulties, this study follows the revenue approach recently applied in the literature (Hadley, 2006; Abdulai and Tietje, 2007; Gaspar *et al*., 2009, Bahta et al, 2015) and defines output as:

$$Q_{i(j)} = \frac{\sum_{T}^{R} y_p}{t} \tag{15}$$

[3] The annual national agricultural survey is continuous program of household surveys, which is specific to the agricultural sector aimed at establishing trends in agricultural production and mode of operation. The main objective of the program is to provide time series of basic information on crop production and livestock population and on related general agricultural data.

where $Q_{i(j)}$ is the annual value of beef cattle output of the ith farm in the j^{th} production system (measured in Botswana Pula[4]); R denotes any of the three forms of cattle output considered, i.e., current stock, sales or uses for other purposes in the past twelve-month period; y is the number of beef cattle equivalents[5]; p is the current price of existing stock or average price for cattle sold/used during the past twelve months; and t is the average maturity period for beef cattle in Botswana, which based on expert consultation is assumed to be four years. Similarly, to ensure that the study captures the approximate share of feeds from different sources, the quantities of purchased and non-purchased (on-farm)[6] feeds were first adjusted in accordance with the average annual number of dry and wet months[7], respectively, in the country.

Average feed prices were computed using the survey's price information collected for purchased feed with further validation by animal nutrition experts in the Department of Agricultural Research (DAR). Both purchased and non-purchased (its value is 0 since no own grown feed is recorded in the data base) feeds were then converted to improved feed equivalents by multiplying the respective feed quantities by the ratio of their prices (or shadow prices) to the average per unit price of improved fodder.

Thus, following Otieno et al (2012) and Bahta et al, (2015), the total annual improved feed equivalent was computed as:

$$\{\varphi\left(p_f * d\right) + S\left(n_p * w\right)\} \tag{16}$$

where; φ and S denote, respectively, the ratio of prices of purchased and non-purchased feed to that of improved fodder; p_f and n_p represent the average quantities of purchased and non-purchased feeds, respectively, in kilograms per month; d is the approximate number of dry months (when purchased feeds are mainly used), while w is the length of the wet season (when farmers mostly use on-farm or non-purchased feeds) in a particular area. Land is measured in terms of arable land in hectares. Agricultural labour measures the total labour cost, including permanent and temporary labour costs. Herd size reflects the stock size and measured in beef cattle equivalents (Otieno et al, 2012 and Bahta et al, 2015). Average annual precipitation data

[4] One Botswana Pula is on average 0.1261 USD (Yahoo Finance (2013).

[5] Following (Otieno et al, 2012; Hayami and Ruttan., 1970; O'Donnell et al., 2008), Beef cattle equivalents were computed by multiplying the number of cattle of various types by conversion factors. Following insights from discussions with BMC (Botswana Meat Commission), the conversion factors were calculated as the ratio of average slaughter weight of different cattle types to the average slaughter weight of a mature beef bull. The average slaughter weight of mature bull, considered to be suitable for beef in Botswana, is between 452-500kg. according to BMC, the average slaughter weights for castrated adult males (oxen>3 years), Immature males (< 3 years), Cows (calved at least once), Heifers(female ≥1yr,have not calved), Male calves (between 8 weeks&<1year),Female calves (between 8 weeks&<1year), , Pre weaning males (<8 weeks), Pre weaning females (<8 weeks) are 400kg, 350kg, 390kg,300kg,250kg, 220kg,95kg and 95 kg, respectively. The calculated average slaughter conversion factors were then: 1.0, 0.86, 0.76, 0.84, 0.65, 0.48, 0.54,0.21 and 0.21, for Bulls, castrated adult males, Immature males , Cows, heifers, Male calves, Female calves, Pre weaning males and Pre weaning females, respectively

[6] No data has been recorded on own grown feed

[7] Botswana is an arid country and according experts information the length of the wet season when farmers mostly use on-farm or non-purchased feeds do not exceed 5 months. Consequently, the study uses 5 wet and 7 dry months, respectively.

is obtained from the Department of Metrological Services for respective year and each district. Except for precipitation, the district level sample weight are used to get a weighted value for the other variables in the production function.

Table 1: Descriptive statistics of production function variables and inefficiency effects

Variables	Mean	Standard Deviation
Value of beef cattle output (Pula)	18004.050	13356.610
Herd Size (in beef equivalent)	27.280	21.632
Feed cost	350.787	1516.161
Purchased feed equivalents (Kg)	608.563	760.156
Labour cost	243.307	192.883
Arable Land area	1.030	0.766
Annual precipitation (mm)	38.283	20.099
Primary education (%)	56.1	0.133
Mortality Rate (%)	14.0	0.177
Proportion of exotic breed	1.6	0.023
Gross offtake rate	4.42	3.583
Non-Farm income	28.4	0.103

Source: Authors' computation using data from Statistics Botswana. (2015).

3.3. Empirical Model

The two common functional forms that are commonly used for empirical analysis in productivity and efficiency analysis are Cobb-Douglas (CD) (*first-order flexible* – it has enough parameters to provide a first-order differential approximation to an arbitrary function at a single point) and translog production (*second-order flexible* form – has enough parameters to provide a second-order approximation) functions (Coelli et al., 2005). Both approaches have their own advantages and disadvantages. For example, some of the disadvantages of CD production function as compared to translog function is that, it imposes restrictions on the production technology, it cannot handle large number of inputs, and it assumes constant returns to scale. However, one of the advantage for the use of CD function is that it can be fitted with very few data points and few parameters, and yet gives good results. On the other hand, the increased flexibility of translog function at times comes at a cost – there are more parameters to estimate, and this may give rise to econometric difficulties such as multicollinearity (Coelli et al., 2005).

Following the principle of *parsimony* which suggest that we should choose the functional form that "gets the job done adequately", hence we choose a CD function. CD is the most suitable given that we have limited sample size and that we need to estimate *J* times the number of parameters compared to the standard stochastic frontier production. C-D function can be mathematically expressed as follows:

$$\ln y_{it} = \alpha_j + \sum_n \beta_j \ln x_{it}\Big|_j + \delta_t\Big|_j t + v_{it} - u_{it}\Big|_j \tag{16}$$

where the α, β's and δ are parameters to be estimated. Whilst subscript *i* denotes agricultural district, *t* is the linear trend that accounts for neutral technical change, *j* denotes the different classes to be estimated, and, whilst *y* and *x* are the logarithms of beef output and a vector of inputs. Following Barros et al (2013) and Mekonnen et al (2015), all explanatory variables have been divided by their geometric mean.

4. Results and discussion

In this section, we present the estimates from LCSF model, the inefficiency model (which is jointly estimated with the LCSF model) and technical efficiency scores and beef production technologies (MTRs) for each class of the agricultural districts in Botswana.

4.1. Latent class stochastic production frontier estimates

Contrary to the previous studies in Botswana that have grouped different production frontiers according to geographic locations e.g., districts (Bahta and Malope, 2014; Bahta et al., 2015), agro ecological regions (Temoso et al., 2015), and production system - traditional versus commercial (Temoso et al., 2016), the present study applies a latent class stochastic frontier (LCSF) approach. The model classifies the 26 agricultural districts into production technology frontiers that corresponds to the beef production system within the model. We avoid *prior* classification of the sample because it may produce biased results since it assumes that all districts in a given region or production system use a similar technology and hence their efficiency is calculated in relation to a similar production frontier (Mekonnen et al., 2015). In this study, to determine the number of classes in which the agricultural districts could be classified into, the Akaike Information Criteria (AIC) and Bayes Information Criteria (BIC) were used (Orea and Kumbhakar, 2004; Alvarez and del Corral, 2010). The AIC is relatively lowest for LCM with two classes, thus implying that is the preferred model than the LCM with three classes. The possible reason for the failure of the LCSF with three classes to converge to the solution is the small sample size (231 observations) for this study.

Table 2 presents the maximum likelihood estimates for the parameters in the stochastic production frontier. All estimated first-order parameters in the LCSF fall between zero and one in both classes and the pooled frontier, thus satisfying a monotonicity condition that all marginal products are positive and diminishing at the mean inputs (with exception of precipitation and labour in class two).

Table 2: Production models for beef production in Botswana, 2006 to 2012

	Latent class stochastic frontiers					
Dependent variable:	Pooled model		Class one		Class two	
Beef Output (Beef value equivalent)	Coefficient	Standard error	Coefficient	Standard error	Coefficient	Standard error
Constant	13.32***	0.061	13.357***	2.558	13.14	539478
Labour	0.035	0.031	0.104	1.257	-0.081	530844
Arable Land	0.109***	0.026	0.093	0.442	0.221	10557
Feed	0.026**	0.012	0.029	0.382	0.011	50630
Herd Size	0.942***	0.040	0.873	0.570	0.902	702016
Precipitation	-0.123**	0.049	-0.087	3.235	-0.289	464483
λ	2.550***	0.423	0.217	121.43	7.686	957300
σ	0.655	0.416	0.711	44.39	0.997	3071
Inefficiency effects						
Primary Education	-3.370***	1.299	-3.581	8.960	-4.974	324400
Mortality rate	1.131**	0.537	2.071	22.06	0.534	104600
Exotic breed	0.084*	0.051	0.049	2.560	0.100	137100
Gross offtake rate	0.326*	0.168	0.204	5.716	0.099	334600
Off-Farm income	0.244	0.524	0.107	24.99	1.749	568500
Observations	231		231		231	

Returns to Scale (RTS)	0.989	1.012	0.764

Source: Author's computation.

The technical inefficiency effects were found to be statistically significant in the stochastic frontier model for beef farmers in both classes. Additionally, the parameters of the inefficiency effects model were found to be significantly different from zero.

In the standard stochastic frontier model (pooled model), herd size, arable land, labour and feed significantly determine beef production output in Botswana. Previous studies on livestock and beef production in Botswana (e.g., Bahta & Malope, 2014; Temoso et al., 2015) have found a positive effect of labour, land, herd size and feed on output. For example, Bahta and Malope (2014) demonstrated that smallholder beef producer profits in Botswana could be increased through increased cropland area and reducing prices of feed products. A possible explanation for this could be that farmers who have more arable land are more likely to have more crop residues they can use to supplement their animals and thus reduce feed costs (Bahta and Baker, 2015).

On the other hand, the precipitation coefficient is unexpectedly negative implying that the precipitation across the agricultural districts had a negative influence on beef production. However, this might rather be interpreted as not as such the high precipitation is negatively influencing beef production, but the extreme rainfall variability. The majority of smallholder beef farmers in Botswana are extensive grazers depending mainly on rain-fed vegetation and the inadequate and poorly distributed rainfall often causes poor pasture growth and may also lead to a decline in fodder supplies from crop residues. Thornton et al (2014) discusses that in dryland countries such as Botswana, droughts and extreme rainfall variability are likely to generate periods of severe feed scarcity which can have devastating effects on livestock productivity and populations. Deficiency in pasture is likely to lead to weight loss and increased deaths of the livestock, forcing farmers to sell their cattle including breeding stock, which forms the basis of beef production and household's wealth to avoid further losses.

Table 2 (bottom row) presents the returns to scale (RTS) for both class one and two agricultural districts and the pooled model, whereby RTS at the district level is equal to the sum of the variables that determines beef production output. For class one beef production technology, the returns to scale (RTS) is slightly larger than unity (1.01), which indicates (on average) the presence of increasing returns to scale at the agricultural district level. Whilst, for class two (0.76) and the pooled model (0.964), the RTS is smaller than unity indicating the presence of decreasing returns to scale. Parameter estimates for λ are significantly different from zero in the pooled model, which implies the presence of inefficiency. The observation row, shows that allocation of the mass of the discrete distribution to the latent classes based on the highest posterior probability of each district in the two technology classes. Approximately 82% of the agricultural districts in our sample belongs to class one, whilst the other 18% belongs to class two.

4.2. Determinants of productivity among smallholder beef producers in Botswana

Technical inefficiency effects model (indicators as inefficiency effects) is presented in Table 2, whereby a negative coefficient indicates that the variable has a negative effect on technical inefficiency (i.e., it has led to an increase in TE). The coefficient of primary education is negative and significant for the pooled model and for both class one and two (although not significant), thus indicating that agricultural districts which have relatively higher rate of farmers with some formal schooling tend to be technically efficient. This implies that the farmers with more education respond more readily in using the new technology and produce closer to the frontier output (Seyoum et al., 1998). These results are consistent with Bahta and Malope (2014) who found a positive relationship between education and productive efficiency amongst the smallholder beef farmers in Botswana. In Kenya, Otieno et al (2012) found that smallholder farmers with formal education and higher income are relatively less efficient.

The table shows that mortality, exotic breed and gross offtake are positive and significant, hence have a negative effect on technical efficiency (at least for the pooled sample). The positive and significant coefficient of exotic breed therefore indicates that, the higher proportion of exotic breed, the less efficient is the agricultural district. This could be due to the lack of adaptation of pure exotic breeds to the very harsh climates of the agricultural districts. Bahta et al (2015) and Temoso et al (2016) found that having less indigenous breeds per herd and more cross breeds is likely to lead to higher beef efficiency. The use of cross breeds has a potential to improve productivity and their suitability to the adverse production environments compared to the indigenous breeds (Temoso et al., 2016). Wollny (2003) also point out that controlled cattle breeding could increase efficiency through improvement of genetic quality, enhancing adaptation of cattle to environmental conditions and ensuring an optimum stocking rate to feed supply within and between years.

The coefficient of gross off-take rate (the ratio of livestock sold to total number purchased and home slaughtered) is positive, indicating efficiency loss from gross off-take rates. Low off-take rates could be attributed to poor management and lack of access to beef marketing facilities

(Temoso et al, 2016). Another possible explanation for this is that smallholder farmers are less commercially oriented and only sell their animals to meet their immediate cash needs and during drought seasons as a drought risk management strategy.

4.3. Technical Efficiency and Technological gap analysis

The kernel densities of the technical efficiency scores for the two classes are presented in Figure 3. Generally, agricultural districts in latent class one are more technically efficient than agricultural districts in latent class two, implying that agricultural districts in class one are more homogenous (Mekonnen et al., 2015). The mean technical efficiency scores for beef production between 2006 and 2014 for agricultural districts in class one is 18 % whereas it is 13 % for agricultural districts in class two. The implication of these results is that there is high potential in both classes of agricultural districts to increase beef production output by 82% and 87% respectively, using the same amount of inputs.

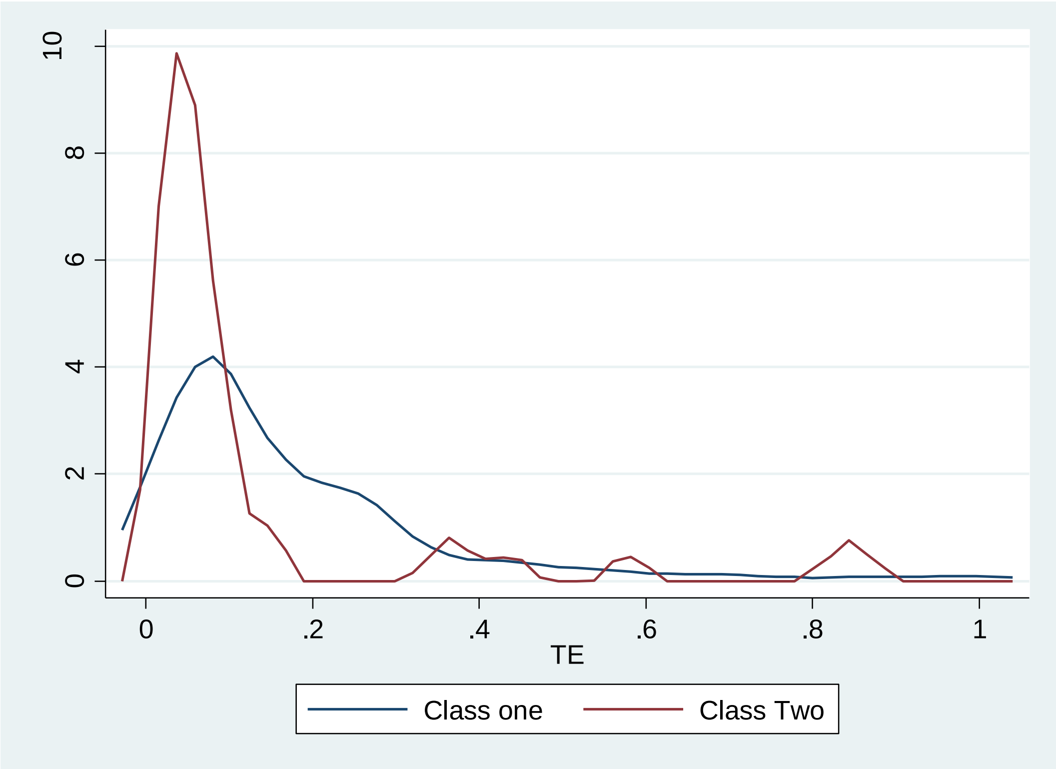

Figure 3: Kernel density of technical efficiency scores for latent classes (Source Authors' computation).

The TE is generally lower than from previous studies, for example, Thirtle et al (2003) estimated an average TE of 25.7 % for the traditional livestock (cattle, goats and sheep), whilst Bahta et al (2015) and Temoso et al (2016) found somewhat higher TE of 49.6% and 79% respectively. However, our results are not directly comparable to previous technical inefficiency estimates which may have been overestimated if technology heterogeneity is present in the sample, but not accounted for in the estimation process. Based on the highest posterior probability the model classified 21 agricultural districts as class 1 and the rest 5 as class 2. The minimum posterior probability of belonging into either class is 0 whereas the maximum is 1 and 0.99 for class 1 and 2, respectively. For the agricultural districts which belong to class 1, the average posterior probability of belonging to class 1 is 99.85% whereas for those that are categorized as class 2, it is about 95%.

Figures 4 and 5 provides the technical efficiency scores of beef production for class one and two agricultural districts estimated respectively (and their distribution across Botswana are also presented in map in Appendix 1).

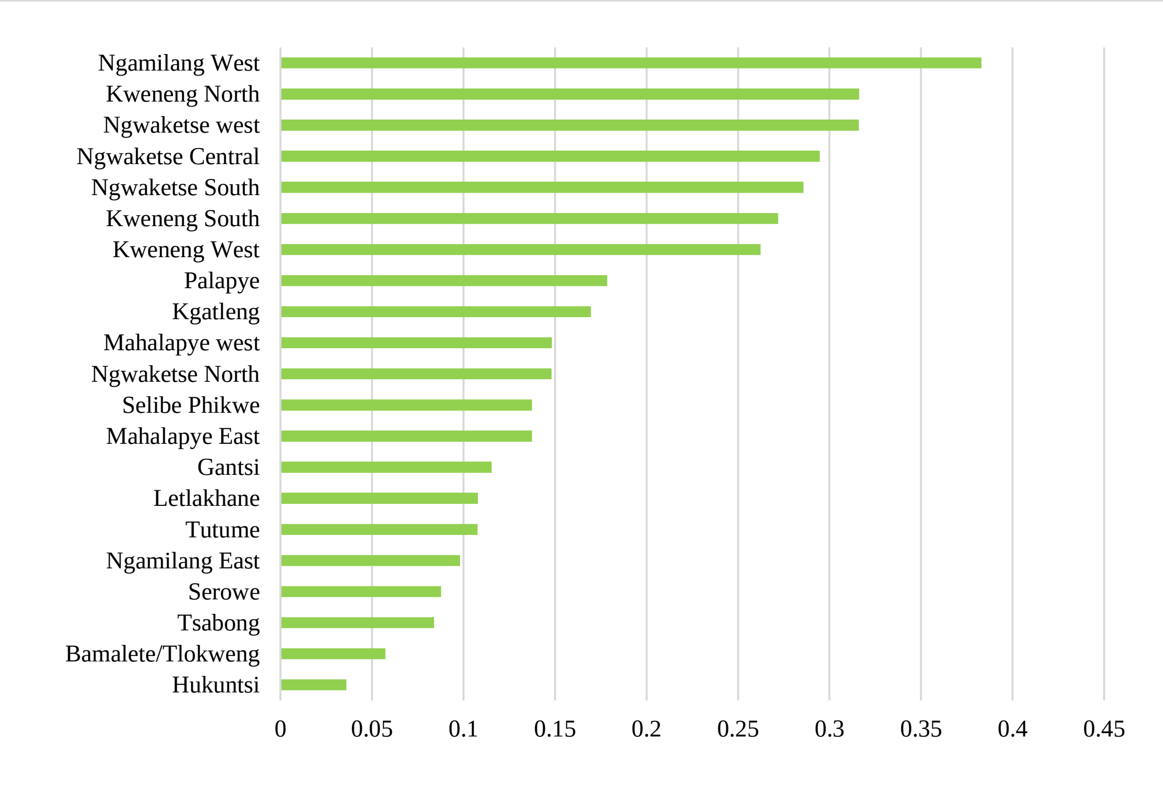

Figure 4: Mean Technical Efficiency Scores for Class One Agricultural Districts (Source: Authors' computation).

Figure 6 and 7 presents the meta-technology ratio scores (MTR) and technical efficiency scores which are estimated with respect to the meta-frontier that encompasses all the class frontiers, thus allowing direct comparison of efficiency of a given agricultural district to any other agricultural district in Botswana.

The MTR measures the technological gap faced by an agricultural district in each class when their performance is compared against any agricultural district in the sample. A higher (lower)

MTR implies a smaller (larger) technology gap between the class frontier and the meta-frontier (MF).

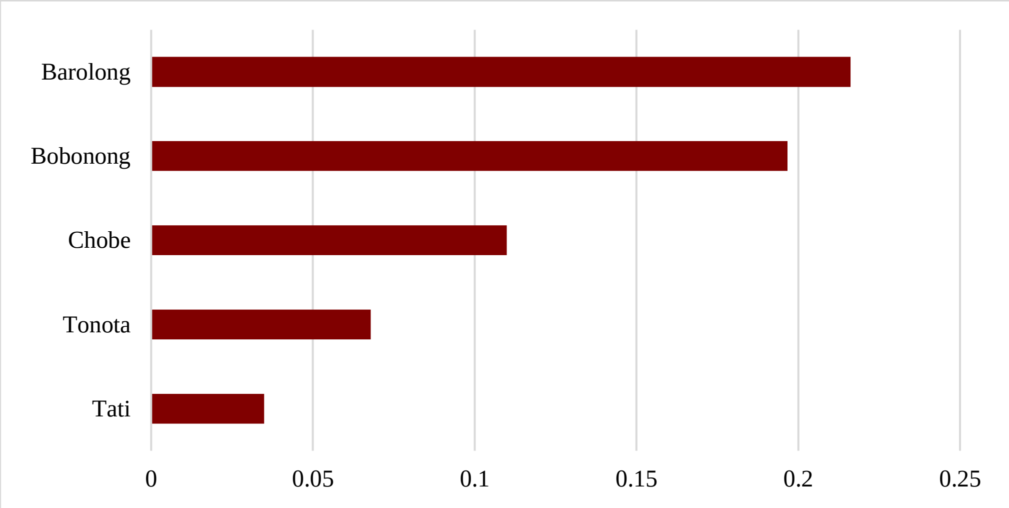

Figure 5: Mean Technical Efficiency Scores for Class Two Agricultural Districts (Source: Authors' computation).

A value of 1 (100%) is equivalent to a point where the class frontier coincides with the MF. According to Figure 6, on average, Class one agricultural districts have a superior beef production technology than class two districts.

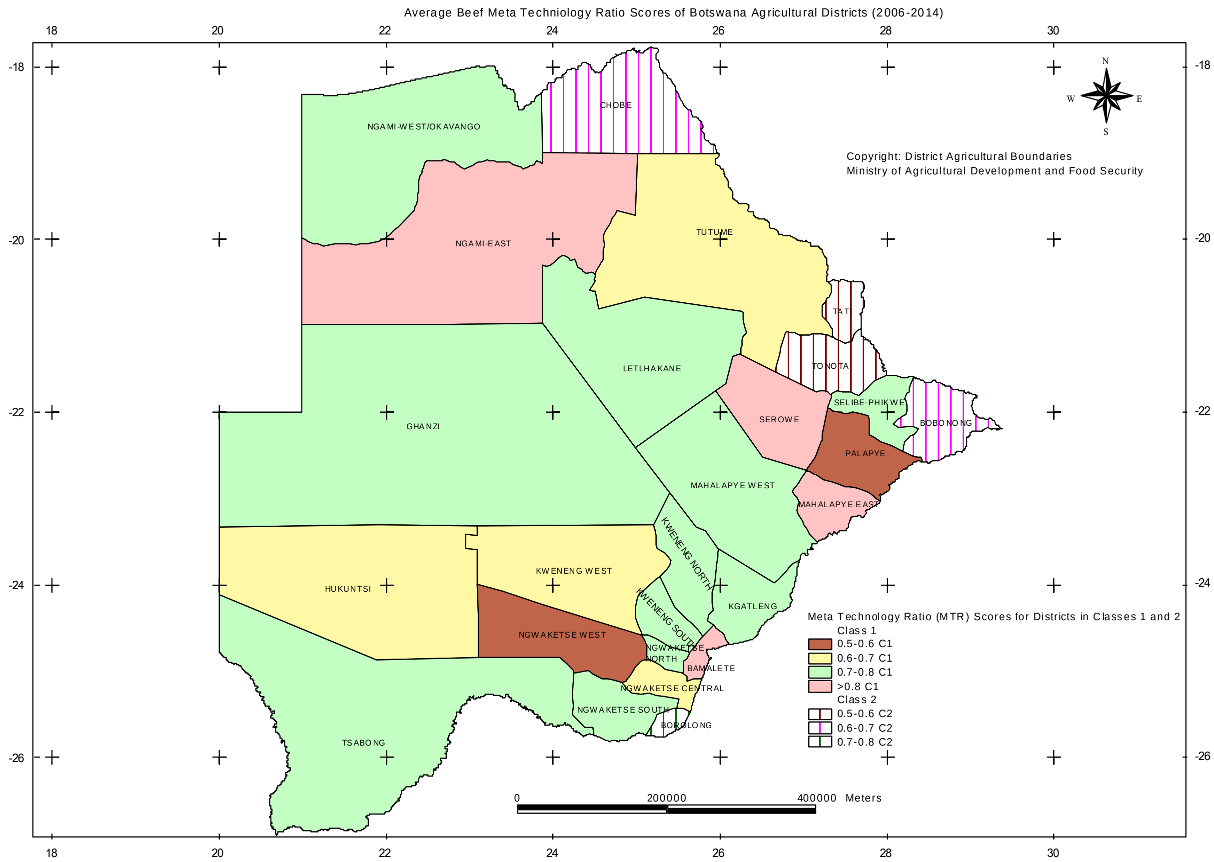

Figure 6: Average Beef Meta Technology Ratio (MTR) Scores of Agricultural Districts in Botswana, 2006 to 2014 (Source: GIS mapping of Authors' computation).

Amongst class one agricultural districts, Ngamiland East, Serowe, Mahalapye East and Bamalete have the highest beef farming technology (MTRs of more than 0.8), whilst Palapye and Ngwaketse East have the least beef farming technology (MTRs of 0.5 to 0.6). In class two, Tati and Tonota have the highest beef production technology (MTRs of 0.7 to 0.8), whilst Chobe and Bobonong have the least (MTRs of 0.6 to 0.7). Most parts of Botswana are disadvantaged by unfavourable environmental conditions and the performance of different sectors within agriculture is closely related to these conditions (Burgess, 2006). The beef farming technology for class one agricultural districts is mainly composed of livestock specialising districts (e.g., Ghanzi, Hukuntsi, Tsabong, Ngwaketse West and Letlhakane), whilst class two is composed of agricultural districts whereby crop suitability is high (e.g., Barolong and Tati) (Burgess, 2006; van Engelen et al., 2013).

Average Beef Meta Technology Efficiency Scores of Botswana Agricultural Districts (2006-2014)

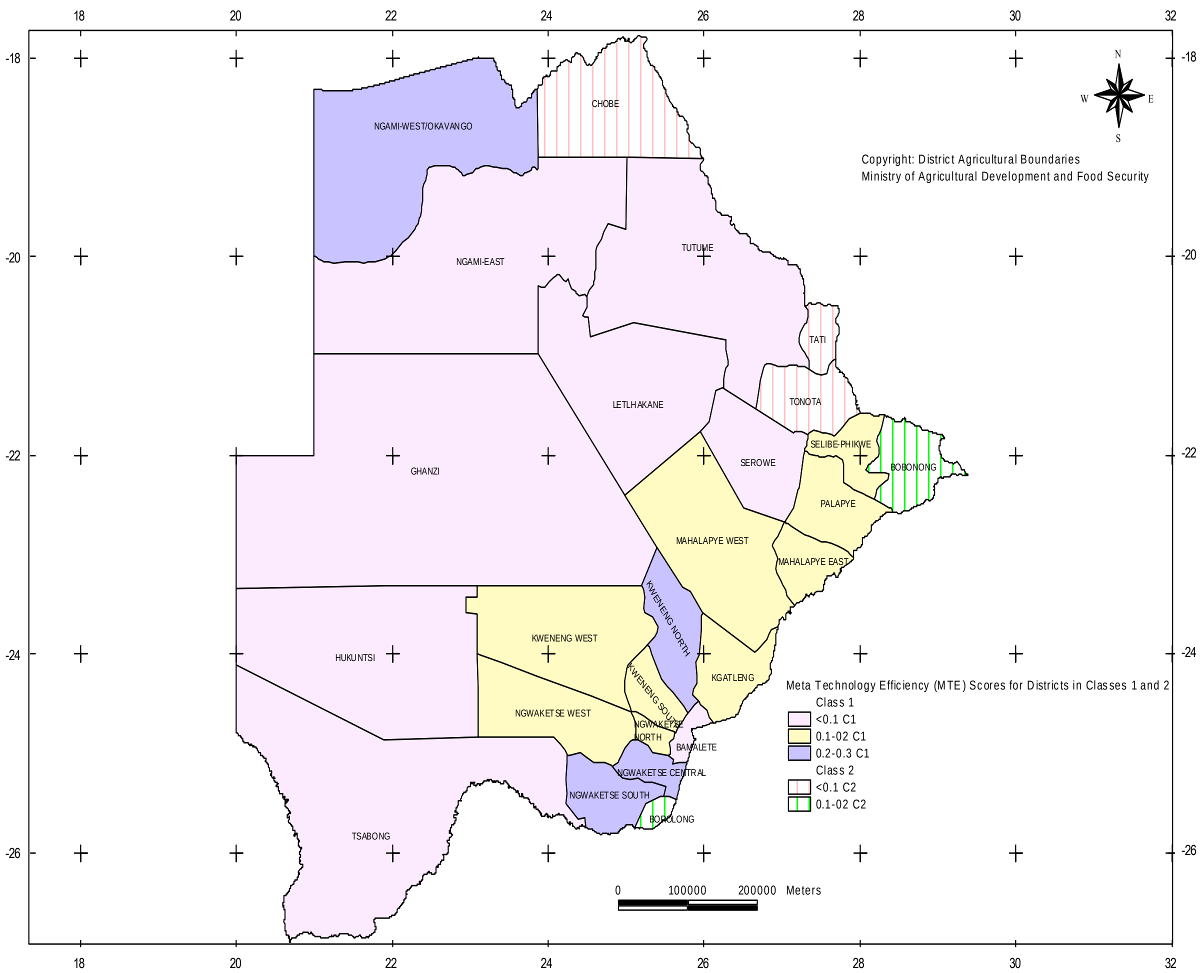

Figure 7: Average Beef Meta Technology Efficiency Scores of Agricultural Districts in Botswana, 2006 to 2014 (Source: GIS mapping of Authors' computation).

Figure 7 shows that technical efficiency scores relative to the meta-frontier (available beef production technology) for class one are on average higher than from class two. Class one is composed of both livestock specialising districts (Ghanzi, Hukuntsi, Ngamiland West, Ngwaketse West etc.) and mixed farming regions (Ngwaketse South, Serowe, Kgatleng), whilst class two is made up of districts with high comparative advantage in arable agriculture. Overall the top performing districts in Botswana are Keening North, Ngwaketse Central, Ngwaketse South and Ngamiland West, three of these four districts are located in the South Eastern part of the country where there are better road networks, access to markets and information, close proximity to extension services and Lobatse, where the main exporting abattoir is located (Temoso et al., 2015).

On the other hand, the least performing districts in Botswana are in class two. This is composed of wildlife and Foot and Mouth Disease (FMD) infested agricultural district (Chobe) and agricultural districts in the FMD intensive surveillance zones 6 and 7 (Tonota and Tati agricultural districts - Zone 6 and Bobonong - Zone 7). In 2011, there was a major FMD outbreaks in Zone 6 and 7 which had a significant impact on beef production and restrictions access to export markets (BMC Abattoirs). Chobe agricultural district has the highest density of wildlife and tree species; hence the majority of the region is composed of wildlife management and forest reserves (Burgess, 2006). Human and wildlife conflict is common in this district and this has significant impacts upon smallholder farmers and consequently has implications for food security as animals destroy crop fields and kill livestock (Temoso et al., 2015). This region is also known as the "red zone" where buffalo carrying foot and mouth disease (FMD) reside (van Engelen et al., 2013). Cattle in this district are vaccinated to prevent infection and they cannot be moved to other regions or traded to other countries.

The implication of these results are that the best performing agricultural districts in Botswana are those that either specialises in livestock production or located in the regions with better road networks, access to markets and information, close proximity to extension services and Lobatse where the main exporting abattoir is located. On the other hand, the least performing districts are either in the FMD restriction zones or have had an outbreak of the disease. These differences suggest the presence of clearly differentiated technologies among smallholder beef producers in Botswana and hence where policies to improve productivity could be focused. This study shows that providing livestock farmers with relevant livestock extension, better roads to enable access to input and output markets would facilitate better use of available technology by the majority of farmers who currently produce sub-optimally. Possible essential interventions would include improving farmers' access to appropriate knowledge on animal husbandry such as cattle feeding methods, disease monitoring and breeding (Bahta et al., 2015).

5. Conclusions and policy implications

This study has demonstrated that there are clear differences in the production technologies, returns to scale and efficiency amongst the agricultural districts in Botswana. The differentiated beef production technologies amongst the agricultural districts in Botswana lends support to the importance of correctly accounting for heterogeneity in order to make correct policy recommendations regarding the beef production and performance. The results of the study indicate that beef output is positively related to availability of labour, the size of arable land, feed availability and herd size. This, therefore calls for policies that promote ownership of arable land in which farmers can plant fodder and or crops residues to feed their livestock. The study has also shown that beef production efficiency is positively associated with attainment of formal education and hence policies that address education and training of smallholder farmers should be pursued.

The study found that mortality and gross offtake rates lead to beef production efficiency loss. This calls for improvement in animal husbandry which includes vaccination against major diseases in order to reduce mortality and training of farmers to undertake beef cattle farming as a commercial activity and hence increase offtake. Farmer training could be achieved through improvement in the extension services.

The study has shown that there are differences in technologies that lead to differences in efficiencies across districts as indicated by the MTR and average technical efficiency scores. The majority of the districts that perform better are those located in areas where there are well developed infrastructure and access to both output and input markets. The policy implications for this is that concerted efforts must be made to improve infrastructure in the farming areas in order to improve market access and hence production efficiency. On the other hand, districts that performed poorly in terms of efficiency are mostly those where there is occurrence of foot and mouth disease, which limits access to the Botswana Meat Commission (BMC) abattoirs. This leads to depressed producer prices and hence loss in efficiency. These districts also have large herds of wildlife which leads to conflicts between wildlife and livestock keepers as the wildlife kills their livestock and in some cases there are carriers of the FMD virus. The implication of this is that better ways of minimising conflicts between wildlife and livestock should be found in order to improve beef production efficiency. The mean technical efficiency scores for both class one and two are very low, 18 and 13% respectively. This implies that there is scope for improvement using the same amount of inputs. To achieve this the above recommendations and other measures should be undertaken.

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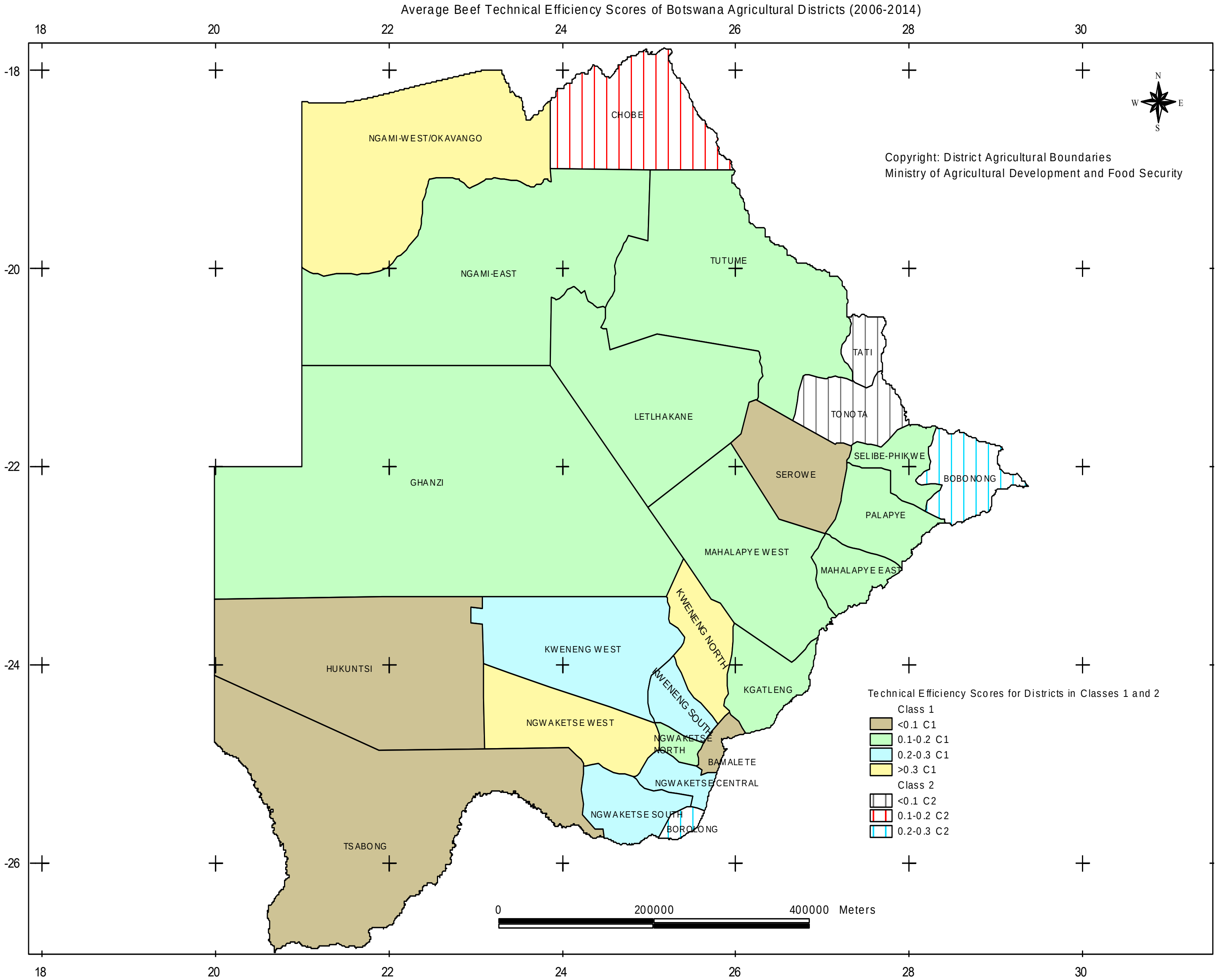
APPENDIX



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