Efficiency of Botswana Meat Commission: An Empirical Approach

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Abstract

This paper investigates the efficiency status of Botswana Meat Commission (BMC), which is a public company. It employs transcendental logarithmic Stochastic Production Frontier to estimate efficiency, and ordered Logit model to ascertain determinants of the efficiency of BMC. Estimation data for the period of study (1979 – 2009) were accessed from the Bank of Botswana, Central Statistics Office and the BMC. The findings indicate that there were inefficiency in BMC of up to around 22%, and the main reasons for this include material inputs constraints (livestock availability), and insufficient penetration into the global market owing to low exchange rate competiveness. The paper ends with some policies implications to deal with these constraints.

Keywords: *Botswana meat commission, efficiency, ordered logit, parametric approach, stochastic frontier*

JEL Classification: D24, P47, O13

1. Introduction

Botswana is commended for having one of the world's highest growing economies over the few past decades. Between 1965 and 2005, real annual economic growth averaged 9% per year. This impressive growth rate has been made possible by the pursuit of sound economic policies. Prior to gaining independence in 1966, Botswana was counted among the poorest countries in the world with an economy that was largely based on agriculture and some tourism. Over the years the contribution of agriculture to gross domestic product (GDP) has declined significantly to less than 3%. Although the contribution of agriculture to GDP is minimal, it contributes a substantial proportion of rural income and 20% of total employment (UNDP, 2009). Agriculture serves as an important source of livelihood for most of the people in Batswana, particularly through cattle farming. According to Stevens and Kennan (2005), cattle production remains an important factor in the rural economy as a

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source of income, employment and investment opportunities. About 25% of rural households derive their livelihoods from cattle. The government of Botswana has since independence developed and implemented policies that sought to improve livestock productivity to maintain and increase beef and beef by-products exports, sustainable diversification of the sector, and employment creation (Mapitse, 2008). Some of those efforts and policies include the establishment of the Botswana Meat Commission (BMC). Halderman and Nelson (2005) argue that the main beef producers and exporters in Africa are Namibia, Botswana and South Africa, which represent models of successful export-led livestock systems in the continent.

The BMC serves as a sole exporter of meat and its by-products, and it also sells directly to retailers in the local market. Botswana had a privilege of free access to the lucrative and protected European Union (EU) market in the past because of the Cotonou Agreement, which expired in 2007. The most attractive market for Botswana beef is in the EU, where the country has its largest trade share of beef exports.

Given Botswana's privileged position, one would assume that supply of cattle at abattoirs would rise significantly and be consistent with the available opportunities. Unfortunately performance of the BMC over the years has been marked with fluctuations, and as a result it was unable to satisfy its EU beef quota of 18,961 tonnes before the Cotonou Agreement expired in 2007 (BEDIA, 2008). Furthermore, the number of cattle supplied to BMC over the years has been declining, while on the other hand domestic consumption has been increasing and local butcheries have attracted an increasing number of cattle for slaughter. Botswana has higher potential of meat production than it actually produces. Nevertheless, BMC production has declined overtime, and this implies that there is underutilisation of this important opportunity. Following these developments, there is a need to determine BMC efficiency and identify possible sources of inefficiency as time goes.

The main objective of the study is to examine the technical efficiency of BMS. Specifically, it examines the performance of BMC from 1979-2009; ascertains efficiency status; and then underlines causes of inefficiency in the Botswana beef industry.

The rest of the paper is organized as follows. Section 2 presents theoretical and empirical perspectives of efficiency analysis. Section 3 describes the methodology used, while section 4 contains empirical analysis. The last section presents conclusions and key policy implications arising from the findings.

2. Theoretical and Empirical Perspectives of Efficiency Analysis

The positive underlying principle that derives efficiency analysis in economics stems from the urge to create and enhance tangible value, while the normative raison d'être for efficiency analysis is founded on the challenge to obtain useful

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policy information. Because value itself may be subjective, Vilfredo Pareto set a condition for efficiency, that: if there is a change which makes at least one individual better off without making any one else worse off, that change is efficient (Debreu, 1959; Varian, 1992; Schenk, 2004). The relationship between cost function and production function, which underlines efficiency assessment, was first established by Shephard (1953, 1970) with assumption of theoretically known efficiency. Quantitative methods for measuring total economic efficiency (with assumption of unknown theoretical efficiency) were pioneered by Farrell (1957). In economic theory there are algebraic and geometric characterisations of production plans that can unambiguously be regarded as non-wasteful (efficient). According to Mas-Colell *et al*. (1995), a production vector $y \in Y$ is efficient if there is no $y' \in Y$ such that $y' \geq y$ and $y' \neq y$. This concept means a production vector y is efficient if there is no other feasible production vector y' that generates as much output as y using no additional inputs. This philosophy is the basis of the illustrative Production Possibility Frontier (PPF), from which the method of analysis used in this study originates.

There are two broad theoretical perspectives of efficiency measurements. According to Le and Harvie (2010), techniques for estimating efficiency are classified into parametric and non-parametric. The parametric method normally uses a stochastic production function which assumes that the error term is composed of two elements. The Stochastic Frontier Analysis (SFA) approach was introduced by Aigner *et al*. (1977) and by Meeusen and van den Broeck (1977). The non-parametric approach is often associated with Data Envelopment Analysis (DEA), which is based on mathematical programming models to estimate the optimal level of output conditional on the amount and mix of inputs (Murillo-Zamorano, 2004).

In the context of our study, parametric approach dwells on the stochastic production frontier, which in a simple form can be written as $Y = f(X_i\beta) + \varepsilon$, where Y is output, $Xi's$ represent inputs, and β is a vector of unknown parameters. The key idea behind the stochastic frontier model is that ε (which is an error term) is composite (Aigner, Lovell & Schmidt, 1977; Meeusen & Van den Broeck, 1977). Therefore this term can be written as, $\varepsilon = v - u$; where v is a two-sided ($-\infty < v < \infty$) normally distributed random error that captures the stochastic effects outside the firms' control, measurement errors, and other statistical noise. The term u is a one-sided ($u \geq 0$) efficiency component that captures the technical inefficiency of the firm, which can be measured as the deficiency in output away from the maximum possible level given by the stochastic production frontier. In other words, u measures the shortfall in output Y from its maximum value given by the stochastic frontier $f(Xi; \beta) + v$; where β represents a set of parameters. Distribution of this one-sided term can be half-normal, exponential or gamma.

Non-parametric approach usually uses DEA method, which assigns a score of 1 to the 100% efficient units, and a score of less than 1 to any inefficient

units. A score reflects radical distance from the estimated reference unit production frontier to the considered decision making units (DMU). The model measures relative performance of decision making units[1] (Charnes, Cooper & Rhodes, 1978; Banker, Charnes & Cooper, 1984). The DEA ratio, which is converted to linear programming model, is presented as:[2]

$$\text{Maximise } ho = \frac{\sum_{r=1}^{s} u_r y_{ro}}{\sum_{i=i}^{m} v_i x_{io}}$$

$$\text{Subject to } \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=i}^{m} v_i x_{ij}} \leq 1; j = 1,2, \dots, n$$

$$\frac{u_r}{\sum_{i=i}^{m} v_i x_{io}} < \varepsilon; r = 1,2, \dots, s$$

$$\text{and } \frac{u_i}{\sum_{i=i}^{m} v_i x_{io}} < \varepsilon; r = 1, \dots, m\ \varepsilon > 0$$

There are n DMUs, which are j = 1,2,….,n. In the model, $y_{rj} > 0$ and $x_{ij} > 0$ represent observed amounts of r^{th} output and i^{th} input of the j^{th} DMU. DMU_0 efficiency score is $0 \leq h_0 \leq 1$ as regards the constraints. $\varepsilon > 0$ is a non-archimedean constant that is smaller than any positive valued real number[3] for $h_{0,}u_{r,}$ and v_i represent visual multipliers obtained by solving the maximisation problem. In the maximization expression, the numerator represents a set of desired outputs, and the denominator represents a set of inputs. Visual output $Y_0 = \sum u_r^* y_{ro}$, is summed over r = 1, 2,...,S. Visual input, $X_0 = \sum v_i^* y_{ro}$, is summed over i= 1, 2, …, m. The obtained $h_o^* = Y_o/X_0$ is efficiency score, which satisfies $0 \leq h_o^* \leq 1$. When h_o^*= 1 represents full (or 100%) efficiency and h_o^*< 1 represents some relative inefficiency.[4]

The choice between these methods is guided by the nature of available data and the type of efficiency being estimated. For long-term time series data, stochastic frontier method seem to be better than DEA because it allows hypotheses testing, which is not the case for the non-parametric DEA.

On the empirical front, there are several studies of efficiency for different sectors in the literature. A number of studies have investigated technical efficiency using stochastic frontier and also DEA. Studies that have applied stochastic frontier approach, which is also selected for this study include, among

[1] A unit can be contextualized in terms of production period for an organization. That is, every period can be taken as independent of the rest and then they are respectively compared to the standard period that is estimated as reference one due to its performance outcome.

[2] This specification is based on the work of Charnes, Cooper and Rhodes (1978) and Banker, Charnes, and Cooper (1984) as the DEA foundational literature.

[3] In practice ε is handled by the software.

[4] Note that the asterisk denotes an optimal h_o and the vectors of u_r and v_i which maximise it.

others, Djokoto (2011) in Ghana, who investigated agriculture sector efficiency using time series data, and established that technical efficiency had a mean of 82%. Others who have recently applied the stochastic frontier technique on agriculture and manufacturing related studies are Le and Harvie (2010) on evaluation of technical efficiency of Vietnamese manufacturing small and medium enterprises for the period 2002-2007; Aggrey *et al*. (2010) on assessment of the relationship between firm size and technical efficiency in East African manufacturing firms; Ray (2006) on the changing role of technological factors in explaining efficiency in Indian firms; and Lopez *et al*. (2006) on technical efficiency of Argentinean dairy farms. A notable similarity in all these studies is that there were some degrees of inefficiency in each case, and both those factors internal to the firms and those external to the firms matter for inefficiency.

In Africa, there have been several studies on efficiency analysis of different sectors. A few include those done in the banking industry (Aikaeli, 2008; Ncube, 2009); in the manufacturing sector (Söderbom & Teal, 2003; Pack 1993; Valenchik, 1997); hospitals performance (Osei *et al*., 2005; Akazili, *et al*., 2008); and analysis relative efficiency between public and private sectors (Hsu, 2010). Overall, these studies show that in Africa inefficiency exists owing to, among others, underutilization of meagre available resources emanating from imbalances between human resources and capital availability. Regarding public sector efficiency, Hsu (2010) show that there are variations in efficiency in African countries resulting from the influence of market conditions and institutional arrangements. On the demand side the relevant factors include constraints related with income levels, population density and low purchasing power of the public sector, which critically influence technical efficiency. On the supply side the input mix through levels of economic development, management of human resources, institutional structures, and the strength of the public sector capacity matter. BMC is in public sector in Botswana, and so may be subject to these same conditions. In Ghana, Hsu (ibid.) provides a number of studies that show the way these factors played role in enhancing inefficiency, especially in the public sector.

The common findings of these studies are that (i) exposure to new technologies (which are mostly foreign for developing countries); (ii) level of human capital development; and (iii) size/level of specialization have positive effect on efficiency (Pitt & Lee, 1981). These studies support the hypothesis that total factor productivity is in tandem with technological improvement. There is evidence that some of firms, and in particular manufacturing industries, have managed to reap benefits of urbanization effects and metropolitan externalities, infrastructure, and information network/ technology to raise their productivity.

3. Methodology

This study uses the stochastic frontier analysis because it fits better to the data and approach of analysis we are undertaking than the DEA. The parametric method specifies a stochastic production frontier, which assumes that the error

term is composed of two elements: (i) statistical noise; and (ii) a disturbance representing technical inefficiency.

Technically, parametric and non-parametric estimations differ in an important way. Parametric methods are classified based on what is known about the population that is being studied. These methods are those for which we know that the population is approximately normal, or it can be approximated using a normal distribution after invoking the central limit theorem. In contrast, non-parametric methods are statistical techniques for which there are no assumptions made about normality for the population that is being studied. These methods do not have any dependence on the population of interest. For that reason, non-parametric methods are also called distribution free methods. Both have their respective merits and demerits, but in opting for any approach, one has to consider the respective methodological relevance given a research problem, types of available data and at times the tractability or convenience.

Stochastic frontier production model was developed independently and simultaneously by Aigner, Lovell and Schmidt (1977), Meeusen and Van den Broeck (MB) (1977), and Battese and Corra (1977). In this model there is a composite error term which is decomposed into a normal stochastic variable that captures the effects of exogenous shocks beyond the control of the analysed units on one hand, and the technical inefficiency on the other, thus making one error term of two components (Murillo-Zamorano, 2004).

The generalised functional form, which is derived from the Cobb-Douglas format of the stochastic production function, can be specified as:

$$Y_i = X_i\beta + (V_i + U_i), i = 1, \dots, N \qquad (1)$$

where, Y_i is the output (or logarithm of production) of the i^{th} firm; X_i is the vector of inputs of the i^{th} firm; β is the vector to be estimated parameters; V_i represent the random variable which is assumed to be independently and identically distributed (*iid*); U_i stands for the random variable which is assumed to account for technical inefficiency in production and usually assumed to be *iid (*Greene, 980).

The maximum likelihood method can be used to estimate the coefficients of the production function. The likelihood function is expressed in terms of the variance parameters of the frontier function:

$$\sigma^2 = \sigma_v^2 + \sigma_u^2 \; and \; \gamma = \frac{\sigma_u^2}{\sigma^2} \qquad (2)$$

Where, σ_v^2 is variance of noise and σ_u^2 is variance of inefficiency effects. If the value of σ^2 is equal to zero, then u_i is also zero, which means that the firms are fully efficient. γ has a value between zero and one, and if it is zero, the deviations from the frontier are attributed to random error. If it has the value

of one, the deviations are due to technical inefficiency. The estimation model in translog[5] stochastic production function form is expressed as:

$$\text{In } Y = \alpha_0 + \sum_{i=1}^{n} \text{In } X_i + ½ \sum_{i=1}^{n} \sum_{j=1}^{n} \beta_{ij} \text{ In } X_i \text{ In } X_j + \varepsilon \qquad (3)$$

Y is output of the firm; and X's are inputs, which include L denoting labour input; K is capital investment; ME is material input. The equation comprises also a random error term ε (which is divided into v and u). v which denotes statistical noise is assumed to be $N(\mu_i, \sigma^2 v)$; and u which represents technical inefficiency is also assumed to be $N(\mu_i, \sigma^2 u)$; while β's are the coefficients.

To estimate factors influencing efficiency, an ordered logit model is employed. Ordered dependent variable is constructed from the efficiency scores, which are limited between 0 and 1 at any one time. That means the variable is dichotomous but allowing more than usual two categories of the logit model. Logit, Probit and Tobit offer relatively similar results, but Logit has a comparative advantage on the basis of simplicity. Gujarati (2003) emphasizes on the issue of simplicity of the Logit model in that the logistic cumulative distribution function is simple, and normally it involves an unevaluated integral that is easy to work with. Another advantage of the Logit model is the interpretability; the linearized inverse transformation of the Logit model $\wedge^{-1}(\pi)$ is directly interpretable as log-odds. The Logit model has been employed by other researchers including Girardone *et al*. (1996) and Ray (2006), *inter alia*, in measuring determinants of efficiency.

The general ordered Logit model is specified as:

$$y^* = x^{'} \beta + \varepsilon \qquad (4)$$

$$\begin{cases} 0 \text{ if } y^* \leq \mu_i, \\ 1 \text{ if } \mu_1 < y^* \leq \mu_2 \\ 2 \text{ if } \mu_2 < y^* \leq \mu_3 \end{cases}$$

Where y^* is the latent variable which is unobservable, and x is a vector of independent variables while β is a vector of regression coefficients to be estimated.

The specified ordered Logit Model to estimate determinants of efficiency is given by:

$$Pr(eff = 1 \mid y^*) = f(L, K, FMD, \pi, Exc£, ExcR, I, Inf, P, MI, Age), \quad (5)$$

where Pr(*eff* =1) means efficiency, *L* represents labour, while *K* denotes capital and *FMD* represents Foot and Mouth Disease. π denotes profit and *Exc£*, *ExcR* represent exchange rate of Pula to Pound and Rand, respectively. *I*

[5] *Translog* stands for transcendental logarithmic

is inventory, and *Inf* is domestic inflation rate. *P* represents price offered by BMC to producers, *MI* is material input, and *Age* is the number of years the commission had been operational by the time.

The efficiency scores are measured by:

$$TE = exp\ (-\ u_t) \qquad (6)$$

Variables and Data

Labour is defined in monetary terms (Pula), and comprises of staff costs that incorporate wages and salaries and social security contributions.

Capital is defined in monetary value (Pula) and comprises of property, plant and equipment employed in the production process.

Material Input is measured in terms of costs (in Pula) of average material input used in the production process. The costs considered are those incurred in livestock and meat purchases by the commission.

Foot and Mouth Disease is defined in terms of a dummy variable. It will take on values of 1 or 0; 1 indicating the presence of Foot and Mouth, and 0 indicating the absence of the disease.

Profit is defined in monetary value (Pula), and it is the net returns of the firm after tax.

Inventory is measured in monetary terms (Pula).

Exchange rate is defined as the price of one currency in terms of the other. The exchange rate considered will be the Pula/Pound and Pula/Rand because largest proportion of output goes to United Kingdom and South Africa, and these rates are ones that matter the most.

Inflation rate it is defined as the rate of change in the consumer price index. Inflation rate is considered because the domestic market accounts for the second largest market of the commission's output after exports to United Kingdom and South Africa.

Price is defined amount of money offered to producers by BMC per 100 kilograms.

Age is the number of years that the commission has been in operation.

The study uses secondary data for the period 1979–2009. The period was selected because of the availability and reliability of its data. The sources of data for exchange rate and inflation were Bank of Botswana and Central Statistics Office. Sources of data for throughput, capital, labour, profits, price and inventory was BMC annual reports. Data on the incidences of the foot and mouth disease were sourced from the Ministry of Agriculture.

4. Empirical Results

The analytical technique used to get these estimates is stochastic frontier analysis for estimation of efficiency, and ordered Logit model for estimation of determinants of efficiency. Important pre-estimation tests of the data when estimating stochastic frontier model is normality test to make sure variables that are estimated together are in normal distribution, especially if normality is the underlying assumption as it is in our case. To ensure validity of the results, this is done before empirical estimations using Jarque-Bera test. Table 1 presents the results.

Table 1: Jarque-Bera: Skewness/Kurtosis Test for Normality

Variable	Observation	Pr(Skewness)	Pr(Kurtosis)	adj chi2(2)	Prob >chi2
Output	31	0.115	0.7758	2.85	0.2404
Capital	31	0.001	0.0104	15.75	0.0004
Labour	31	0.102	0.2758	4.07	0.1309
Material Input	31	0.071	0.0998	8.46	0.0145

Source: Authors' Estimation

As regards skewness and kurtosis, the null hypotheses state that distributions of the sample data have no skewness (either to the right or left), and are also not humped, i.e., they are normal. If the tests are significant we will reject the hypothesis, otherwise we accept that they are normally distributed. The results indicate that capital and material input are significant at 5% level, and so they are not normally distributed. In order to make the variables normally distributed, they are all together transformed into natural logarithms according to the requirement of the stochastic frontier model, and then normality is tested again. Table 2 presents the results.

Table 2: Jarque-Bera: Skewness/Kurtosis Test for Normality

Variable	Observation	Pr(Skewness)	Pr(Kurtosis)	adj chi2(2)	Prob >chi2
lnoutput	31	0.4854	0.3090	1.64	0.4409
lncapital	31	0.1073	0.7836	2.91	0.2331
lnlabour	31	0.1938	0.2564	3.26	0.1964
lnmaterial Input	31	0.6033	0.1838	2.21	0.3314

Source: Authors' Estimation

After transformation all the variables, they are not statistically significant at 5% level, therefore they are normally distributed. Subsequent to ensuring normality, the Translog Production Function (Equation 3) is estimated, and the results are presented in Table 3.

Sigma u is statistically significant at one percent level and thus, the null hypothesis of absence of random inefficiency effects; $\theta_u^2 = 0$ is rejected. The value of sigma u indicates the variation away from the production frontier is due

to technical inefficiency. Sigma u of 0.216 testifies that there is about 22% of the variations away from the production frontier due to technical inefficiency.

Labour and material input are both significant at 5% level. The estimates of the translog model imply that the coefficients of elasticities of both labour and

Table 3: Stochastic Frontier Model Estimates

Stoc. Frontier normal/half-normal mpdel — Number of obs = 31
Log likelihood = 19.528979 — Wald chi2(3)= 59.64
Prob > chi2 = 0.0000

lnoutput	*Coefficient*	*Std. error*	*z*	$P > \|z\|$	*Level of Significance*
Capital	-0.0604328	0.052511	-1.15	0.250	
Labour	-0.3636901	0.1253039	-2.90	0.004	**
Material input	0.4204189	0.1343154	3.13	0.002	**
_cons	11.94637	0.6570264	18.18	0.000	
/lnsig2v	-6.131983	1.033995	-5.93	0.000	*
/lnsig2u	-3.066312	0.3691017	-8.31	0.000	*
sigma_v	0.0466076	0.024096			
sigma_u	0.2158534	0.0398359			
sigma2	0.0487649	0.0161746			
lambda	4.63129	0.056046			

Notes: Likelihood-ratio test of sigma_u = 0: chibar2 (01) = 1.89 Prob>=chibar2 = 0.084
*, **, and*** denote significance level at 1%, 5% and 10%respectively.

material input are output inelastic, this indicating decreasing returns to scale. 1% increase in labour leads to 0.36% decrease in output, and a 1% increase in material input leads to 0.42% increase in output.

To identify determinants of efficiency using ordered Logit model, efficiency indexes are predicted from the estimates of the stochastic frontier model by using the distribution of inefficiency term σ_u conditional on ε (equation 6; see Appendix I). Efficiency indices are then used to estimate the ordered Logic models (equation 5) whose results are shown in Table 4.

Table 4: Ordered Logit Model Estimates of the Determinants of Efficiency

Efficiency	**Coefficient**	**Std. error**	**Z**	**P > Z**	**Level of Significance**
FMD*	0.7863446	2.24192	0.35	0.726	
Inventories	5.847105	3.951719	1.48	0.139	
Price	27.32007	12.796	2.14	0.033	**
Material	-45.45422	16.86211	-2.70	0.007	**
Pula /Rand	-40.77002	23.22552	-1.76	0.079	***
Pula/Pound	-42.501	22.82131	-1.86	0.063	***
Inflation	10.03909	8.500279	1.18	0.238	
Years	-0.404809	0.7642718	-0.53	0.596	

/cut1[6]	-112.189	50.96601
/cut2	-104.7014	49.27894

Notes: (*) *dy/dx* is for discrete change of dummy variable from 0 to 1
*, **, and*** denote significance level at 1%, 5% and 10%respectively.

Table 4 shows that producer price, which is set by the commission, is significant at 5% with a positive coefficient. A rise in the producer price leads to an increase in inefficiency. When price increases it means the commission incurs more cost in purchasing cattle from farmers, thus reducing the commission's returns, other things remaining unchanged.

Material input is also significant at 5% level and has a negative coefficient. Material input is the value spent on materials used in the production process, i.e. the costs incurred in livestock purchases by the commission. The results imply that a rise in the value spent on material input will result in a reduction in inefficiency or increase in efficiency. Increased material input leads to a rise in throughput which improves efficiency of the commission, this reflecting more output.

The Pula/ Rand and Pula/ Pound exchange rates are significant at 10% level. These exchange rates measure how much Pula is demanded per the respective unit of foreign currency. The coefficients are both negative implying that an increase in exchange rate (depreciation of the domestic currency) leads to a decrease in inefficiency. When domestic currency depreciates it means the commission's throughput becomes cheaper or more affordable, hence improving its competitiveness in the world market. The improved competitiveness in turn leads to increased demand, which prompts the commission to increase throughput leading to higher efficiency.

5. Conclusion and Policy Implications

The results show that the Botswana Meat Commission is technically inefficient as 22% of the variations away from the production frontier are due to technical inefficiency. Further, the results show that producer price raises inefficiency of the commission, while increase in material input and depreciation of the Pula reduces the inefficiency of BMC. Given the importance and potential that the beef sector possesses in terms of employment, diversification of the economy and export earnings, the key implicated policy options are: (i) to open up the market, i.e., put in place a more competitive environment; and (ii) to increase the processing of beef by-products (horns and leather) as a way to diversify and maximize from the material inputs overall.

[6] Cut1 and Cut2 are thresholds or cut points, they reflect the predicted cumulative probabilities at covariate values of zero. These are ancillary parameters which represent cut points of the oredered varibale against the dividing criterion. For example, if in the distribution one has values less than Cut1 these could be counted as low, between Cut1 and Cut2 as medium and above Cut2 as high.

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Appendix I: Efficiency Scores of Botswana Meat Commission

Years	Efficiency Scores	Efficiency Scores*100
1979	0.7998163	79.98
1980	0.6072663	60.73
1981	0.777606	77.76
1982	0.8987265	89.87
1983	0.9314193	93.14
1984	0.9597105	95.97
1985	0.936064	93.61
1986	0.968035	96.80
1987	0.711702	71.17
1988	0.6901546	69.02
1989	0.7948694	79.49
1990	0.8148555	81.49
1991	0.9466271	94.66
1992	0.9791399	97.91
1993	0.8344826	83.45
1994	0.8716086	87.16
1995	0.9038035	90.38
1996	0.8016614	80.17
1997	0.7011493	70.11
1998	0.9387005	93.87
1999	0.8335138	83.35
2000	0.9369683	93.70
2001	0.9399002	93.99
2002	0.7408608	74.09
2003	0.928544	92.85
2004	0.8952304	89.52
2005	0.8153254	81.53
2006	0.9231052	92.31
2007	0.9363417	93.63
2008	0.7221383	72.21
2009	0.7351124	73.51