DUAL TECHNOLOGICAL DEVELOPMENT IN BOTSWANA AGRICULTURE: A STOCHASTIC INPUT DISTANCE FUNCTION APPROACH

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ABSTRACT

To improve the welfare of the rural poor and keep them in the countryside, the government has been spending 40% of the value of agricultural GDP on agricultural support services. But can investment make smallholder agriculture prosperous in such adverse conditions? This paper derives an answer by applying a two-output six-input stochastic translog distance function, with inefficiency effects and biased technical change to panel data for the 18 districts and the commercial sector, from 1979 to 1996. This model demonstrates that herds are the most important input, followed by draft power, land and seeds. Multilateral indices for technical change, technical efficiency and total factor productivity (TFP) show that the technology level of the commercial sector is more than six times that of traditional agriculture and that the gap has been increasing, due to technological regression in traditional agriculture and modest progress in the commercial sector. Since the levels of efficiency are similar, the same pattern is repeated by the TFP indices. This result highlights the policy dilemma of the trade-off between efficiency and equity objectives.

JEL classification: O4, Q1
Keywords: smallholder, commercial, agricultural efficiency, Botswana

INTRODUCTION

Botswana is a landlocked southern African country, bordered to the south and east by South Africa and Zimbabwe and to the west and north by Namibia. With an area of 566,000 square kilometres and a population of only about 1.5 million, the population density is unusually low at 2.6 persons per square km (World Bank, 2002). However the carrying capacity is also low, since the soils are mostly poor and the climate semi-arid, with frequent droughts, so the vast majority of the land is better suited to cattle ranching than arable agriculture. Indeed, in the past, beef exports (mainly to the European Union) were the major source of foreign exchange, but diamonds (Botswana is the world's leading exporter in value terms) and tourism are now more important. Although the discovery of diamonds has rescued Botswana from its former position as one of the poorest countries on earth, mining provides little employment, so the wealth is not shared and the real importance of agriculture is that it is still the main source of income for approximately half the population.[1] Since it accounts for less than five percent of GDP (World Bank, 2002), it is clear that the agricultural population is relatively poor and the distribution within the sector is also extremely unequal. About half the farm families own no cattle at all, while the politically well connected have accumulated large herds. However, the diamond revenue allows the government to spend as much as forty per cent of agricultural GDP on support schemes that are intended to improve the welfare of the agricultural population and keep them in the rural areas, despite the very harsh conditions (Thirtle et al., 2000).[2]

This paper investigates the effectiveness of this expensive support program, a question tackled by Seleka (1999) who investigated the performance of traditional arable agriculture in Botswana for the 1968-90 period. His conclusion was that government support to the sector had a positive effect on the welfare of rural households but was unsustainable, and that agricultural productivity actually declined over the study period.

The first contribution of our paper is to fill a gap in the existing literature by evaluating the productivity performance of the whole of Botswana agriculture. Arable agriculture (the sub-sector studied by Seleka (1999)) accounts for only around 10% of agricultural GDP, so this study also covers animal production and the growing commercial sector.

The second contribution is to demonstrate the advantages of the parametric distance function approach to characterising the agricultural technology and decomposing productivity growth in the context of a low-income country. The only prior example of use of distance functions for this purpose is Brümmer et al. (2002) who investigated farm-level productivity growth in dairy production in three European countries. The empirical model is a two-output stochastic input distance function that is used to analyse agriculture efficiency and productivity in the eighteen districts of Botswana and the commercial sector, for the period from 1979 to 1996. The approach is appropriate, first because it requires only data on outputs and inputs, which are well recorded, whereas markets for the major inputs, such as land and labour, are not sufficiently developed for there to be meaningful prices.[3] Second, it accounts for noise, which is an advantage over non-parametric methods such as DEA. Third, tests show that the crop and animal sectors cannot be aggregated, which rules out the use of stochastic production functions to estimate the technology and efficiency levels. By contrast, distance functions can accommodate multiple inputs and outputs. The method produces output and input elasticities and leads to the estimation of indices for technical change, technical efficiency and total factor productivity. This allows the commercial sector to be compared with traditional agriculture.

The remainder of the paper is organized as follows. Section two discusses the theory and section three very briefly describes the data. The results are reported in section four, beginning with tests to determine the appropriate model. Section five presents the efficiency and productivity indices and the final section concludes by summarising the results and suggesting further developments.

THE INPUT DISTANCE FUNCTION: DEFINITION, PROPERTIES AND INTERPRETATION

The input distance function first introduced by Shepard (1970) is defined on the input requirement set $L^t(y)$ as:

$$D_i^t(x,y)=Max\{\rho: x/\rho \in L^t(y)\} \tag{1}$$

It measures the largest factor of proportionality by which the input vector x can be scaled down in order to produce a given output vector y with the technology existing at a particular time t. For any input-output combination (x,y) belonging to the technology set, the distance function takes a value no smaller than unity, while a value of unity simply indicates technical efficiency. More generally, the distance function provides a measure of technical efficiency since its reciprocal is the well-known Farrell (1957) input-based index of technical efficiency.

The input distance function is always homogenous of degree one in inputs and inherits properties from the parent technology as detailed in Färe and Primont (1995).[4] Most useful for the interpretation of the empirical estimates is the duality between the cost and input distance functions, which is easily expressed as:

$$C^t(w,y) = \underset{x}{Min}\{wx : D_i^t(x,y) \geq 1\} \tag{2}$$

From this minimisation problem, where w denotes a vector of input prices, it is straightforward to relate the derivatives of the input distance function to the cost function. First, with respect to input levels x_k, one obtains:

$$\frac{\partial D_i^t(x^{*t}(w,y),y)}{\partial x_k} = \frac{w_k}{C^t(w,y)} = r_k^{*t}(x,y) \tag{3}$$

Hence, the derivative of the input distance function with respect to a particular input k is equal to the cost-deflated shadow price of that input $r_k{*}^t$, which is therefore expected to take a positive value.[5] The previous equality is more conveniently expressed in terms of the log derivative of the distance function:

$$\varepsilon_{D_i^t,x_k} = \frac{\partial \ln D_i^t}{\partial \ln x_k} = \frac{w_k x_k^{*t}(w,y)}{C^t(w,y)} = S_k^t \tag{4}$$

Equation (4) states that the log derivative of the input distance function with respect to input k is equal to its cost share S^t_k. It therefore captures the relative importance of that input in the production process, a property that we use to interpret our estimation results. With respect to the output vector y, application of the envelope theorem to minimisation problem (2) leads to the following equality:

$$\varepsilon_{D_i^t, y_m} = \frac{\partial \ln D_i^t(x^{*t}(w,y),y)}{\partial \ln y_m} = -\frac{\partial \ln C^t(w,y)}{\partial \ln y_m} \quad (5)$$

The elasticity of the input distance function with respect to any output is therefore equal to the negative of the cost elasticity of that output. It is expected to be negative for all desirable outputs and, in absolute value, reflects the relative importance of each output.

Finally, and most importantly for our purpose, the distance function can easily inform the researcher on the evolution of the technology over time. For analytical tractability, this paper follows Chambers (1988) in assuming that a stable relationship exists between outputs, inputs and time, or:

$$D_i^t(x,y) = D_i(x,y,t) \quad (6)$$

Once again, straightforward application of the envelope theorem to minimisation problem (2) leads to:

$$\varepsilon_{D_i^t, t} = \frac{\partial \ln D_i\ (x^*(w,y,t),y,t)}{\partial t} = -\frac{\partial \ln C(w,y,t)}{\partial t} \quad (7)$$

Hence, the elasticity of the input distance function with respect to time is equal to the elasticity of cost reduction and provides a dual measure of the speed of technical change. A negative value for this elasticity indicates technological regression and a positive value technological progress. This analysis can be pursued further, by considering a Hicksian-style definition of technical change bias based on the relative factor shares expressed in equation (4):

$$B_{kt} = \frac{\partial S_k^t}{\partial t} = \frac{\partial^2 \ln D_i}{\partial \ln x_k \partial t} \quad (8)$$

A positive (negative) value of B_{kt} indicates that technical change is biased in favour of (against) input k.

Finally, note that the distance function can be used to derive virtually all the classical properties of the underlying technology, such as returns to scale and measures of input and output substitutability (Färe and Primont (1995), Grosskopf et al. (1995), Morrison Paul et al. (2000), Kim (2000)). Constant returns to scale are defined in terms of the distance function by:

$$\forall \lambda > 0,\ D_i(x,\lambda y,t) = \lambda^{-1} D_i(x,y,t) \quad (9)$$

The other properties of the distance function are not developed, since they are not used in this application.

An Estimable Model

The value of the distance function is not observed so that imposition of a functional form for $D_i(x,y,t)$ does not permit its direct estimation. A convenient way of circumventing this problem was suggested by Lovell et al. (1994) who exploit the property of linear homogeneity of the input distance function, expressed mathematically as:

$$D_i(\lambda x,y,t) = \lambda D_i(x,y,t)\ \forall \lambda>0 \quad (10)$$

Assuming that x is a vector of dimension K and setting $\lambda=1/x_1$, where x_1 denotes its (arbitrarily chosen) first component, the previous equation is expressed in logarithmic form as:[6]

$$\ln D_i(x,y,t) = \ln x_1 + \ln D_i(x/x_1, y, t) \quad (11)$$

Similar reasoning is used to establish that imposing CRS implies the following relationship:

$$\ln D_i(x,y,t) = \ln x_1 - \ln y_1 + \ln D_i(x/x_1, y/y_1, t) \quad (12)$$

The next stage of the analysis relies on the idea that the logarithm of the distance function in (11) measures the deviation of an observation *(x,y,t)* from the deterministic border of the input requirement set *L(y,t)* which, following the stochastic frontier literature, is itself explained by two components. The first one corresponds to random shocks and measurement errors that can take either positive or negative values and are described by a symmetric error term *-v*. The second one corresponds to technical inefficiencies that are also assumed to be stochastic and are captured by a non-negative random variable *u*. At a conceptual level, the presence of inefficiencies can in turn be justified by a non-uniform distribution of managerial skills across the population of firms using the same technology. Mathematically, the previous assumptions are summarized by:

$$\ln D_i(x,y,t) = u - v \tag{13}$$

Equations (11) and (13) are now combined to give:

$$-\ln(x_1) = \ln D_i(x/x_1,y,t) - u + v \tag{14}$$

If CRS is imposed, we obtain a slightly different expression:

$$-\ln(x_1)+\ln(y_1) = \ln D_i(x/x_1,y/y_1,t) - u + v \tag{15}$$

Given a parameterisation of the distance function and distributional assumptions on the random terms, the previous equations (14) or (15) can be estimated by the maximum likelihood methods that have now become commonplace in the stochastic frontier literature (summarised in Coelli, Rao and Battese, 1998). All models consider that the random error terms v are iid and follow a normal distribution $N(0,\sigma^2_v)$ but differ with respect to the distribution of inefficiencies u. Extending the seminal model of Aigner, Lovell and Schmidt (1977), Battese and Coelli (1995) relax the assumption of identically distributed inefficiency terms in order to identify the determinants of technical inefficiencies and it is this model that we use in the empirical application. Accordingly, it is assumed that the stochastic terms u_{it} are obtained by truncation at zero of a normal variable $N(\mu_{it};\ \sigma_u^2)$ where:[7]

$$\mu_{it} = z_{it}\delta \tag{16}$$

The term z_{it} denotes a vector of observable explanatory variables while δ is a vector of parameters to be estimated. In this context, the likelihood function can be expressed algebraically and maximised numerically to produce estimates of both the input distance function and the vector of parameters δ. Further, while the individual inefficiency levels are not directly observable, the method allows for calculation of their predictors expressed as (Coelli and Perelman, 1996):

$$TE_i^P = 1/D_i^P = 1/E[\exp(u_i)\,|\,v_i - u_i] \tag{17}$$

Functional Form

The translog is used because imposing linear homogeneity in inputs is not possible for the other flexible functional forms and the Cobb-Douglas violates the convexity condition, as well as being too restrictive. The model with *K* inputs and *M* outputs therefore takes the following form:

$$\begin{aligned}\ln D(x,y,t) = {} & \alpha_0 + \sum_{k=1}^{K}\alpha_k \ln x_k + \sum_{m=1}^{M}\beta_m \ln y_m + \varepsilon_t t + \frac{1}{2}\sum_{k=1}^{K}\sum_{k'=1}^{K}\alpha_{kk'} \ln x_k \ln x_{k'} + \\ & \frac{1}{2}\sum_{m=1}^{M}\sum_{m'=1}^{M}\beta_{mm'} \ln y_m \ln y_{m'} + \frac{1}{2}\varepsilon_{tt}t^2 + \sum_{k=1}^{K}\sum_{m=1}^{M}\gamma_{km} \ln x_k \ln y_m + \sum_{k=1}^{K}\gamma_{kt} t \ln x_k + \sum_{m=1}^{M}\gamma_{mt} t \ln y_m\end{aligned} \tag{18}$$

The conditions for linear homogeneity in *x* are:

$$\sum_{k=1}^{K}\alpha_k = 1; \forall k, \sum_{k'=1}^{K}\alpha_{kk'} = 0; \forall m, \sum_{k=1}^{K}\gamma_{km} = 0; \sum_{k=1}^{K}\gamma_{kt} = 0 \tag{19}$$

The empirical application models regional, rather than farm level, production and it is therefore preferable to impose constant returns to scale (CRS) on the technology. The implied restrictions for the translog are:

$$\sum_{m=1}^{M}\beta_m = -1; \forall m, \forall m', \sum_{m=1}^{M}\beta_{mm'} = \sum_{m'=1}^{M}\beta_{mm'} = 0; \forall k, \sum_{m=1}^{M}\gamma_{km} = 0; \sum_{m=1}^{M}\gamma_{mt} = 0 \tag{20}$$

Using the two sets of restrictions (19) and (20) produces an estimable equation, which is the special case of equation (15) for the translog:

$$-\ln x_1 + \ln y_1 = \alpha_0 + \sum_{k=2}^{K} \alpha_k \ln x^*{}_k + \sum_{m=2}^{M} \beta_m \ln y^*{}_m + \varepsilon_t t + \frac{1}{2}\sum_{k=2}^{K}\sum_{k'=2}^{K} \alpha_{kk'} \ln x^*{}_k \ln x^*{}_{k'}$$

$$+\frac{1}{2}\sum_{m=2}^{M}\sum_{m'=2}^{M} \beta_{mm'} \ln y^*{}_m \ln y^*{}_{m'} + \frac{1}{2}\varepsilon_{tt} t^2 + \sum_{k=2}^{K}\sum_{m=2}^{M} \gamma_{km} \ln x^*{}_k \ln y^*{}_m + \sum_{k=2}^{K} \gamma_{kt} t \ln x^*{}_k + \sum_{m=2}^{M} \gamma_{mt} t \ln y^*{}_m - u + v \quad (21)$$

where x_k* denotes the 'normalised' input quantity x_k/x_1 and y_m*$=y_m/y_1$ denotes the 'normalised' output quantity y_m/y_1. We further impose symmetry of the distance function by setting:

$$\forall k, \forall k', \alpha_{kk'} = \alpha_{k'k}; \forall m, \forall m', \beta_{mm'} = \beta_{m'm} \quad (22)$$

Given the dual nature of Botswana agriculture, a dummy variable D is added to allow the technologies to differ in level in the two sectors and a cross-term between the dummy variable and the time trend allows different paths of technological change in the two sectors. This gives the full model as:

$$-\ln x_1 + \ln y_1 = TL(x^*, y^*, t, \alpha, \beta, \varepsilon, \gamma) + \phi_D D + \phi_{Dt} Dt - u + v \quad (23)$$

The limited data available restricted the choice of inefficiency effects and in the end three variables were selected: a time trend, a cross-term between the commercial dummy and the time trend and finally the output mix p:

$$\mu_{it} = \delta_0 + \delta_t t + \delta_{dt} D_{it} t + \delta_p p_{it} \quad (24)$$

This specification allows inefficiencies to vary over time, but in a possibly different manner in the two sub-sectors.

DATA

The detail of how the data set was built is given in Annex 1. All series are for 1979 to 1996, giving a panel of 342 observations. Note that what is referred to as year t corresponds in fact to the agricultural season between year t and year $t+1$ and that it is also how the results are reported in the empirical section of the paper. The outputs are crops and livestock and the components were aggregated using constant (1995) price weights, so these series are equivalent to physical quantities of output. The input series include six different factors of production, which are either measured in physical units (land, labour and draft power) or are constant (1995) price aggregates (seeds, fertilisers and herds). The output mix variable p was simply defined as the revenue share of livestock in total output.

RESULTS

Tests of hypotheses for model selection

Alternative specifications of the model were evaluated using generalised likelihood ratio tests, which compare the likelihood functions under the null and alternative hypothesis, represented by the model described in the last section.[8] Table 1 first reports the test that compares the frontier with the mean input distance function, estimated by considering that the inefficiency term u is non-stochastic and equal to zero. In this context, any deviation from the frontier of the input requirement set is solely explained by random shocks and the distance function can be conveniently estimated by ordinary least squares. The significant drop in the likelihood function associated with this model, from –5.34 to –43.35, implies a clear rejection of the null hypothesis. This is confirmed by the significantly large value of parameter γ in Table 3 (0.95) that indicates that most of the deviation from the deterministic border of the input requirement set is due to technical inefficiencies rather than random shocks. Hence, significant technical inefficiencies exist in Botswana agriculture.

Table 1. Tests of Hypothesis.

Null Hypothesis Ho	Parameter Restrictions	Log-Likelihood (Ho)	Log-Likelihood (H1)	λ	Critical Values 5% (1%)	Outcome
Mean DF	$\gamma=\delta_0=\delta_t=\delta_{Dt}=\delta_p=0$	-43.35	-5.34	76.02	10.37 (14.33)	Reject 1%
No Inefficiency Effects	$\delta_t=\delta_{Dt}=\delta_p=0$	-38.77	-5.34	66.86	7.82 (11.34)	Reject 1%
Input-Output separability	$\gamma_{km}=0$, all k, all m	-13.89	-5.34	17.10	11.07 (15.09)	Reject 1%
Cobb-Douglas	$\alpha_{kk'}=\beta_{mm'}=\gamma_{km}=\phi_{kt}=\phi_{mt}=0$ all k, all m	-179.91	-5.34	349.14	41.34 (48.28)	Reject 1%
No Commercial Dummies	$\phi_D=\phi_{Dt}=\delta_{Dt}=0$	-103.56	-5.34	196.45	7.82 (11.34)	Reject 1%
Neutral TC	$\gamma_{kt}=0$, all k, $\gamma_{mt}=0$, all m	-13.09	-5.34	15.51	12.59 (16.81)	Reject 5%

The second test determines whether the variables introduced as inefficiency effects improve the explanatory power of the model. The null hypothesis is rejected at the 1% level, implying that the distributions of inefficiencies are not identical across individual observations but depend on the variables included in vector z_{it}. This result gives strong support to the inefficiency model of Battese and Coelli (1995) as opposed to the simpler models of the older literature. The third test is on the separability of the inputs and outputs in the input distance function. This hypothesis is defined mathematically by equating all cross-terms between inputs and outputs (γ_{km}) to zero. These restrictions are strongly rejected, which implies that it is not possible to aggregate consistently the two outputs into a single index. This is why the distance function is used rather than a stochastic frontier production function, which requires output aggregation prior to estimation.

Then, the translog functional form is tested against the null hypothesis that the Cobb-Douglas represents an acceptable approximation of the true input distance function and again the null is rejected, implying that the restrictions imposed by the Cobb-Douglas are inappropriate. The fifth test focuses on the dual nature of Botswana agriculture by considering the null hypothesis that all three parameters associated with the commercial sector dummy variable are simultaneously equal to zero. This is rejected, implying that the two sub-sectors have different technological characteristics that will be investigated further in the next section. Finally, the last test relates to the hypothesis that technological progress is cost-neutral, meaning that it does not affect factor shares. This proposition is rejected at the five percent level of significance.

Altogether, the results of these specification tests point to the complexity of technological relationships in Botswana agriculture: technical inefficiencies are significant, inputs and outputs are not separable, the Cobb-Douglas which is restrictive in terms of substitution possibilities is not appropriate, technological change is biased and there is evidence of important differences between traditional and commercial agriculture. We now turn to the estimation results in order to characterise the technology and its evolution over time.

Distance function results

The results are reported only for the model selected on the basis of the tests. The important parameter estimates are reported in Tables 2 and 3, while the remaining parameters are relegated to Annex 2, Table A1. Together the tables show that out of the 44 estimates, 22 are statistically significant at the 5% level.[9] The several significant cross product and squared terms in Table A1 show why the test rejected the Cobb Douglas as inadequate.

Table 2. Elasticities of input distance function at sample mean.

	Output Elasticities		Input Elasticities					
	Animals	Crops	Seeds	Land	Herds	Fertiliser	Draft Animals	Labour
Parameter	β_l	β_c	α_s	α_a	α_h	α_f	α_d	α_L
Value	-0.90	-0.10	0.07	0.11	0.75	-0.07	0.21	-0.07
t-statistic	-70.16	-	1.52	1.81	14.38	-3.88	4.22	-

Next, the parameter estimates can be interpreted in light of the theory developed in the first section. All the variables were mean differenced prior to estimation so that the elasticities of the distance function with respect to input quantities, output quantities and time estimated at the sample mean correspond simply to the first order coefficients.

Equation (5) established that the elasticity of the distance function with respect to each output corresponds to the negative of the cost elasticity of that particular output. Table 2 reports that, as expected, these two elasticities are negative and highly significant. Hence, increasing production of either of the two outputs results in a substantial increase in cost. The estimates also indicate that the cost elasticity of livestock output (0.90) is much larger than the corresponding elasticity for crops (0.10). This result means that a 10% increase in livestock output results in a 9% increase in total cost, while the corresponding figure for crops is only 1%. Hence, the estimates clearly reflect the dominance of livestock production in Botswana agriculture.

The elasticities of the distance function with respect to input quantities are equal to the cost shares and therefore reflect the relative importance of the inputs in the production process. Table 2 reveals that four of the six elasticities are positive, as expected, with reasonable levels of statistical significance. The elasticity with respect to herd size is largest with a value of 0.75 that means that the cost of that input represents 75% of total cost at the sample mean. This is not an unexpected result given the importance of livestock production in Botswana agriculture. Draft power comes next in terms of cost share with a value of 0.21, a result that suggests that soil preparation is crucial for crop production in Botswana. Land is obviously an important factor of production in agriculture and it is reflected by an elasticity of 0.11, which is statistically significant at the 10% level. Finally, the seed input has a positive elasticity equal to 0.07.

Contrary to theoretical expectations, the model also produces two small negative elasticities, for fertiliser and labour input. The fertiliser result can be explained by the fact that Botswana agriculture is dominated by extensive ranching, with very little use of chemical fertiliser, relative to the (unrecorded) extensive use of animal manure. The insignificant elasticity of labour must reflect the low opportunity cost and productivity of smallholder labour, but is also partly caused by collinearity with herd size and land area.

DUAL AGRICULTURAL DEVELOPMENT: EFFICIENCY OF TRADITIONAL AND COMMERCIAL AGRICULTURE

Insights from the regression results

The specification tests established that there are substantial technological differences between the commercial and traditional sectors. Table 3 shows that the parameter of the commercial dummy variable in the distance function has a positive value of 1.93 and is highly significant. The exponent of this parameter, which is 6.9, can be interpreted as the ratio of the commercial and traditional distance functions, meaning that compared to the traditional technology, the commercial technology can produce the same output with less than one sixth the inputs.[10] This is an important result that suggests that there is a huge technological gap between commercial and traditional agriculture. This large gap is consistent with the limited evidence available for arable agriculture. Seleka (1999) reports that average yields for six different crops in the commercial sector over the 1979-93 period were between two and a half and eleven times those for traditional farming.[11]

Table 3. Technology in traditional and commercial agriculture.

	Technological level	Technological Change		Technical Efficiency				
				Average	$\sigma_u^2/(\sigma_u^2+\sigma_v^2)$	Inefficiency Effect Parameters		
	Commercial Dummy	Time trend	Time x Dummy			Time trend	Time x Dummy	Share Livestock
Parameter	ϕ_D	ε_t	ϕ_{Dt}		γ	δ_t	δ_{Dt}	δ_p
Value	1.933	-0.031	0.079	0.850	0.954	-0.256	0.519	-0.058
t-statistic	15.71	-4.87	3.99	-	71.23	-4.28	18.21	-3.93

Next, we analyse how the technologies evolved over time in the two sub-sectors. The theory section shows that the derivative of the input distance function with respect to time is equal to the elasticity of cost reduction and therefore provides a convenient dual measure of the rate of technological progress.

Table 3 reports a value of –0.031 for the parameter ε_t,, which implies that the traditional sector of Botswana agriculture has undergone technological regression from 1979 to 1996, at the rate of 3.1% per annum.

The elasticity of cost reduction in the commercial sector evaluated at the sample mean is equal to $\varepsilon_t+\phi_{Dt}$, where the second item is the coefficient of the cross-term between the commercial dummy and the time trend in the distance function. The estimate of 0.079 for ϕ_{Dt} in Table 3 means that the commercial sector has undergone technological progress at a rate of 4.8% (7.9%-3.1%) per annum over the period. Thus, the technological gap between traditional and commercial agriculture in Botswana is not only large but also increasing quickly, as the difference in rates of technological change in the two sub-sectors is almost 8% over the period.

Table 3 then reports that the overall mean level of technical efficiency in the sample is 85%, which is coincidentally also the mean efficiency level in the two sub-sectors. Once the difference in technological levels is taken into account, the two sectors are therefore largely similar in terms of technical efficiency. More interesting is the evolution of the efficiency indices over time. First, the coefficient of the time trend, introduced as an inefficiency effect (δ_t in equation (24)) takes a negative and highly significant value. Consequently, as time goes by, the mean of the normal distribution that is truncated at zero to represent inefficiencies in the traditional sector becomes more negative, which signals an improvement in technical efficiency. Hence, this result suggests that the traditional sector operates progressively closer to its technological frontier, which is not surprising since we have just established that this frontier is itself regressing.

In the commercial sector, the evolution of inefficiencies over time follows a different pattern since the coefficient of the cross term between the dummy variable and the time trend in the inefficiency component is statistically significant at the 1% level. For this sector, the effect of the time trend is reflected by the sum $\delta_t+\delta_{Dt}$, which takes a positive value, indicating a progressive decrease in efficiency. Finally, the last column of Table 3 demonstrates that farms with a relatively large output share of livestock tend to be more efficient than farms specialising more heavily in crop production.

In summary of this section, the results show technological dualism between the commercial and traditional sectors. At a static level, there exists a major technological gap between the two sub-sectors, with the commercial sector performing much better than its traditional counterpart. There is also no sign that this situation is improving since, to the contrary, the traditional sector appears to have experienced a slow technological regression over the study period, while simultaneously the commercial sector was experiencing technological progress. This pattern of technological change explains the evolution of technical efficiencies. The traditional sector tends to operate progressively closer to its regressing frontier, while in the commercial sector there is evidence that inefficiency has increased.

Technical Change, Technical Efficiency and TFP Indices

The results reported above are averages over the full period at the sample mean and do not take account of some important aspects of the model, such as the biases of technological change.[12] The magnitude of the efficiency changes over the whole period and their impact on productivity also remain to be quantified. Thus, we now present indices of technical change, technical efficiency and total factor productivity (TFP), which provide a full account of the way in which agriculture has developed in Botswana. The technology index is obtained by chaining the indices of annual technological change calculated from equation (7)[13] while the efficiency scores are the predictors described in equation (17). The chained TFP index is then simply the product of the two other indices.

Table 4 begins by reporting multilateral technical change indices. The commercial sector is given the conventional arbitrary starting value of 100. The first result of the last section was that the commercial sector was, on average, 6.9 times more efficient than traditional agriculture. Thus, the average of the technology index for the traditional sector is set at 14.5 (penultimate row), which gives a starting value of 19.8. With the biases of technological change taken into account, there is technological regression in traditional agriculture of –2.88% per annum, while the commercial sector technology improves at 1.42% per annum (last row). This is consistent with the results of the previous section but the differences in factor proportions in the two sub-sectors tend to reduce the rate of technological divergence between the two sectors.

Table 4. Technology, efficiency and productivity indices.

Year	Technical Change		Technical Efficiency		Total Factor Productivity	
	Traditional	Commercial	Traditional	Commercial	Traditional	Commercial
1979	19.80	100.0	80.8	91.8	16.0	91.8
1980	18.84	98.6	81.3	87.9	15.3	86.7
1981	17.90	99.0	77.6	90.0	13.9	89.2
1982	17.00	100.6	80.2	92.4	13.6	93.0
1983	16.22	100.8	78.6	88.2	12.7	88.9
1984	15.55	99.6	84.2	91.3	13.1	91.0
1985	15.01	99.3	89.6	94.1	13.4	93.5
1986	14.51	99.2	89.5	95.2	13.0	94.5
1987	13.94	100.3	83.1	89.5	11.6	89.8
1988	13.38	103.6	87.5	90.8	11.7	94.1
1989	12.91	108.6	88.5	83.9	11.4	91.1
1990	12.55	113.6	88.4	86.5	11.1	98.3
1991	12.30	117.3	82.7	42.5	10.2	49.9
1992	12.17	118.8	87.8	90.9	10.7	107.9
1993	12.05	119.5	86.2	84.9	10.4	101.6
1994	11.99	121.4	89.0	54.8	10.7	66.5
1995	12.03	124.2	86.3	88.6	10.4	110.0
1996	12.05	127.1	89.5	87.8	10.8	111.6
Average	14.5	108.4	85.0	85.1	12.2	91.6
Annual % Change	-2.88	1.42	0.60	-0.26	-2.30	1.16

The annual results in Table 4 show that for the commercial sector there was stagnation in the first part of the period, followed by growth, as the government began major technological support projects. This pattern is more easily discerned in Figure 1, which plots the series. The commercial sector growth rate from 1987 is an impressive 2.7% per annum, but the table and figure show that the very expensive efforts to aid smallholders, such as the Accelerated Rainfed Arable Programme, considered by Seleka (1999), did nothing more than stop the regression of technology in the smallholder sector, where there is still no growth. Since the commercial sector is 97% ranching, these programmes have concentrated on infrastructure improvements, such as drilling boreholes, although there have been efforts to improve stock and veterinary services.[14]

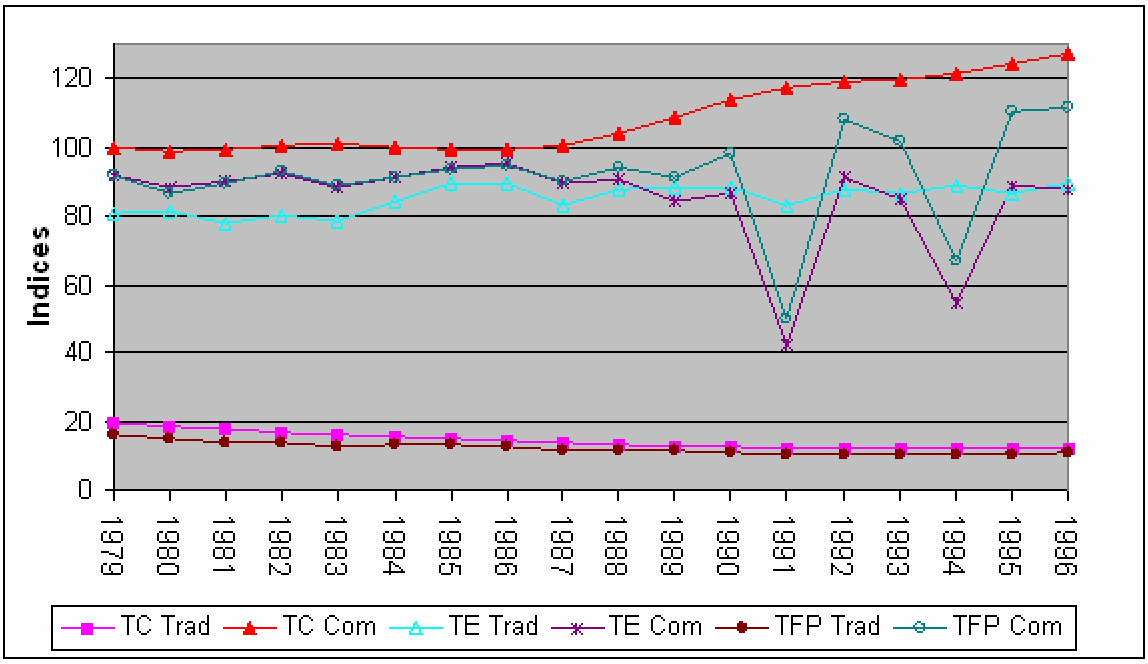

Figure 1. Productivity growth and its components.

The technical efficiency indices differ far less, with traditional agriculture only about 10% worse than the commercial sector at the start of the period. Then, confirming the results of the last section, efficiency improves in traditional agriculture, which can be explained in part by the regressing frontier. However, the annual figures in Table 4, plotted in Figure 1, suggest that weather conditions (droughts) also influence technical efficiency in traditional agriculture and are responsible for relatively large and sudden decreases in years such as 1987 and 1991. Many of the smallholder programmes are a matter of drought relief, such as distributing free animal feed to prevent slaughter in bad years. The payoff, in terms of maintaining the livelihoods of the poor may be substantial, but the cost of these modest efficiency gains, of 0.60% per year, is considerable.

The technical efficiency series for the commercial sector shows the droughts even more clearly and theses account for much of the efficiency losses, but there is also some increase in inefficiency over time, at 0.26% per annum, which suggests that some producers are not assimilating the new technologies and are falling behind the advancing frontier.

Last, the TFP indices are the product of the technical change and technical efficiency indices and, as the figure shows, they follow similar paths to the efficiency indices, because technical change is smoother and more gradual. This combination of technical and efficiency changes results in a TFP for traditional agriculture that falls from a value of 16, to 10.8, which is a decline of 2.3% per annum. Thus, despite all the programmes, the smallholder's productivity has declined over the full period, although the results for the last five years suggest that this trend has now come to a halt. The commercial sector has stagnating TFP in the early period, but does seem to have made rapid progress in the second half of the study period. The annual growth rate for the full period is only 1.16%, but from 1989, it is 2.94% per annum, driven by rapid technological progress.

If this rate of growth can be maintained, the prospects for commercial agriculture in Botswana are good, but there is a clear case of dualistic development. Despite massive support programmes, which may well be excellent in equity terms, the efficiency of traditional agriculture has not improved at all. Seldom has the trade-off between equity and efficiency objectives resulted in such a clear policy dilemma.

CONCLUSIONS

Botswana has used diamond revenues to support agriculture, which accounts for only 4% of GDP, but supports about half the population. This paper studies the efficiency effects of these programmes, using a two-output distance function frontier model, with dummies for the commercial sector and inefficiency effects, which was selected on the basis of extensive tests. The data are a panel of 342 observations, for 18 regions and the commercial sector, over the period from 1979-96, which are sufficient to support this reasonably sophisticated model. The results show that there is a huge technology gap between traditional agriculture and the commercial sector, which is more than six times as technologically advanced. Despite the efforts of the government to improve the livelihoods of the poor smallholders, their level of productivity has fallen, while the commercial sector, which specialises heavily in cattle ranching, has progressed. Hence, almost 40 years after the independence, and despite major investments to support smallholders, agriculture in Botswana has become increasingly dualistic.

The results show that past agricultural policies have not been successful in efficiency terms and have made little contribution to the process of economic development. Naturally, these policies can be justified on equity grounds but the results seem rather unsatisfactory in view of the high level of government support to agriculture, which would be clearly unsustainable without diamond revenue. The policies amount to providing a safety net for smallholders and ameliorating many of the effects of the harsh and variable climate. This is laudable, but the lack of technological progress in the traditional sector suggests that there is little scope for improving the technologies of the resource poor. Those with no cattle are unlikely to prosper with a few smallstock and low yielding grain crops.

The Ministry of Agriculture continues to introduce new policies that differ from those of the past. The NAMPAADD[15] programme launched in October 2002 focuses on the arable and dairy sectors and has the explicit aim of trying to 'enable traditional farmers to transform to commercial farming' and to target incentives to 'beneficiaries and areas where they guarantee a positive change to farm productivity' (Ministry of Agriculture, 2003). Whilst it is hard to argue against commercialisation as the way to improve the incomes of subsistence producers, the scope for this in arable and dairy farming is limited to a few areas. The majority of the country is suitable for little but ranching and no other agricultural activity seems particularly viable. For commercialisation to be based around cattle ranching, the government needs to design schemes to spread ownership to more of the rural population, or ensure that the benefits from larger herds spill over to the locals who do not have cattle.

ACKNOWLEDGEMENTS

The authors are grateful to the Department for International Development for funding this study and Oxford Policy Management for organizing it. The staff of the Department of Agricultural Planning and Statistics, Ministry of Agriculture, Botswana contributed to the data collection and provided local expertise. We particularly thank Howard Sigwele, Mrs K Molefhi and Stephen Ackroyd.

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ANNEX 1:

DATA

The output and input data series required for the estimation were mainly obtained from the key sources listed below. Some series were recovered from the computerized database of the Central Statistical Office (CSO) and others were provided by the Botswana Agricultural Marketing Board (BAMB). All series are for 1979 to 1996, unless otherwise stated, and as mentioned earlier, what is referred to as year *t* corresponds in fact to the agricultural season between year *t* and year *t+1*.

Livestock

Production: Sales and home slaughter: Number of Cattle, Sheep and Goats for the 18 districts and 6 regions, from the Botswana Agricultural Census Reports and Botswana Agricultural Statistics, CSO, (1979-1996).
Labour: Livestock labour use per average herd of Cattle, Sheep & Goats from Farm Management Surveys (Department of Agricultural Planning and Statistics (DAPS), various years).
Herds: Number of Cattle, Sheep and Goats by district and region from Botswana Agricultural Census Reports and Botswana Agricultural Statistics (CSO, 1979-1996).

Crops

Production: Total production in tonnes of Sorghum, Maize, Millet, Beans/pulses by district and region from the Botswana Agricultural Census Reports and Botswana Agricultural Statistics (CSO, 1979-1996).
Labour: Total labour used for ploughing and planting by district and region from Botswana Agricultural Statistics (CSO, 1979-93).
Seed: Seed Planted: Kg/Ha of sorghum, maize, millet, beans/pulses planted by district and region from Botswana Agricultural Statistics (CSO, 1979-93).
Fertilizer: Total fertilizer used by district and region (CSO Internal Data, 1979-96)
Area: Area planted by district and region of sorghum, maize, millet, beans/pulses by district and region from Botswana Agricultural Census Reports (1979-93) and Botswana Agricultural Statistics (CSO, 1979-1996)
Draft Power: Total number of oxen and donkeys from Botswana Agricultural Census Reports (various years) and Botswana Agricultural Statistics (CSO, 1979-1996).

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ANNEX 2:

Table A1: Other parameter estimates

Parameter	Estimate	t-ratio
α_0	0.142	4.017
α_{ss}	0.048	0.739
α_{aa}	-0.127	-1.388
α_{hh}	0.105	1.097
α_{ff}	-0.027	-2.155
α_{dd}	0.121	1.384
β_{ll}	-0.009	-3.493
ε_{tt}	0.002	1.768
α_{sa}	-0.140	-1.438
α_{sh}	-0.317	-2.719
α_{sf}	-0.049	-1.413
α_{sd}	0.176	1.913
γ_{sl}	-0.014	-0.585
γ_{st}	-0.033	-2.511
α_{ah}	0.308	2.182
α_{af}	0.168	2.744
α_{ad}	-0.313	-2.845
γ_{al}	-0.046	-1.681
γ_{at}	0.020	1.402
α_{hf}	0.096	1.727
α_{hd}	-0.191	-1.154
γ_{hl}	0.022	1.048
γ_{ht}	0.021	1.108
α_{fd}	0.009	0.213
γ_{fl}	-0.001	-0.080
γ_{ft}	-0.007	-1.510
γ_{dl}	-0.071	-2.782
γ_{dt}	0.001	0.058
γ_{lt}	-0.003	-1.062
δ_0	1.084	2.814
LLF	-5.339	
σ^2	0.727	3.828

Notes:

[1] FAOSTAT reports an agricultural labour force of 300,000 in 2000 from a total labour force of 673,000. For the same year, the agricultural population was 686,000 and the non-agricultural population 855,000.
[2] This level of expenditure would be impossible without the diamond revenue. Four per cent would be a more usual level, so supporting a sector to this extent is most unusual; but then Botswana is an unusual country.
[3] This prevents the estimation of dual cost and profit functions, which have the additional drawback of imposing restrictive behavioural assumptions.
[4] In particular, as described in Hailu and Veeman (2000), the input distance function is non-decreasing and concave in inputs and non-increasing and quasi-concave in outputs.
[5] $x^{*t}(.)$ denotes the vector of cost-minimising input quantities.
[6] The notation x/x_1 is used to denote the K-1 vector of ratios x_k/x_1, for $k\neq 1$.
[7] The individual and time subscripts i and t were ignored up to this point for clarity.
[8] That is, we compute the statistic $\lambda = -2[\ln LH(H_o) - \ln LH(H_1)]$, where $LH(.)$ denotes the likelihood function, H_0 the null hypothesis and H_1 the alternative hypothesis. Under the null, this statistic follows a chi-squared distribution with a number of degrees of freedom equal to the number of restrictions. The estimation results are usually reported in terms

of parameters $\sigma^2=\sigma_u^2+\sigma_v^2$ and $\gamma=\sigma_u^2/\sigma^2$ rather than in terms of the original variances. If the null hypothesis involves parameter γ, which as a ratio of two variances is necessarily positive, the test statistic follows a mixed chi-squared distribution and the critical values can be found in Kodde and Palme (1986).

[9] The subscripts used to report the coefficient estimates are *l* for livestock, *c* for crops, *s* for seeds, *a* for land, *h* for herds, *f* for feeds, *d* for draft animals and *L* for labour. Note that Table 2 does not report t-ratios for the elasticities of the distance function with respect to crops and labour. This is so because the values of these parameters are inferred from the restrictions expressed in (19) and (20).

[10] It is straightforward to establish that the values of the distance function in the two sectors D_c and D_{tr} are related by the following expression for any input-output combination: $D_c(x,y,0)/D_{tr}(x,y,0)=exp(□_D)$. This ratio measures the difference in technological levels between the two sectors. In particular, suppose that the input-output combination (x, y) is technically efficient for the traditional sector, i.e. $D_{tr}(x,y,0)=1$. The input distance function for the commercial sector takes a value of $exp(□_D)$ which is strictly greater than unity since $□_D$ is strictly positive. Hence, in order to produce the output vector *y*, the input vector *x* could be scaled down by using the commercial technology.

[11] Hence, for maize, average yields in the commercial and traditional sectors were equal to 723 and 66 kg/ha respectively.

[12] For instance, if a particular region makes relatively more use of a factor against which technological change is biased, that region will experience relatively slow technical change.

[13] The exact method of calculation is similar to that used by Coelli et al. (1998), page 234, for a stochastic production frontier.

[14] There have also been programmes to develop irrigated arable agriculture, such as fruits and vegetables, in the commercial sector, but these are not included in the national statistics and require separate evaluation.

[15] National Master Plan for Arable Agriculture and Dairy Development.