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MEASURING THE RETURNS TO PUBLIC SECTOR CROP R&D IN TANZANIA, 1970-99

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This paper is the first attempt at a Malmquist total factor productivity (TFP) index for maize and wheat production in Tanzania, for the period 1970-1999. Productivity grew at 1.4% per annum, due to improvements in efficiency of 2.5% per annum, combined with technological regression at -1% per year over the period. An evaluation of the effectiveness of public sector R&D investment in wheat and maize productivity shows that R&D investment has had a rate of return (ROR) of between 57 and 64% for both crops over the period.

1. INTRODUCTION

There is now a vast amount of empirical evidence on growth in productivity as well as the contributions of domestic research efforts in determining productivity growth in the agricultural sector. These studies have generally been used to determine the effectiveness or value for money of domestic agricultural research policy, in order to justify public sector R&D investment in the agricultural sector. Indeed, empirical studies in both the developed and developing countries have generally advocated support for public sector R&D investment based on market failure arguments and the evidence that the ROR to such investments were high and indicative of under-investment in the sector (Echeverria, 1990). But to date no such information has been available for Tanzania. Thus, for the first time, this paper presents empirical evidence on the rate and sources of productivity growth for wheat and maize in Tanzania, with particular attention focused on estimating the ROR to public sector investment.

This paper does three things. First, it estimates a Malmquist productivity measure for wheat and maize. Second, the Malmquist TFP index is decomposed into its technical and efficiency change components. Third, productivity change is then explained by the lagged effects of public agricultural R&D. The outline of this paper is as follows. The second section provides an overview of previous evaluations of the effectiveness of public

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sector R&D in Tanzania. This is followed by an outline of the theoretical framework and notes on the data in section 3. Section 4 presents the productivity indices for wheat and maize. Section 5 provides evidence of the ROR to maize and wheat R&D. Section 6 concludes by summarising the findings of the paper.

2. PREVIOUS STUDIES

Previous attempts to evaluate the benefits of agricultural research in Tanzania have focused on what has been called the public relations approach. The approach tends to focus on research efforts that describe in general terms what the research has accomplished and/or what the research effort is expected to accomplish in the future. Thus, the evaluation of agricultural research in Tanzania has tended to be qualitative, and progress orientated, for example, toward the development of a new disease-resistant variety of maize, new agronomic practices, etc. Alternatively, the public relations approach may strive for more quantitative methods of research evaluations. These often take the form of crude methods such as quantifying the output gain resulting from the higher yields made possible by research.

The social benefits of agricultural research are implicitly assumed in the public relations approach. This is not the same as the empirical determination of whether or not the allocation of scarce government resources to specific sectors or activities has been beneficial to the Tanzanian economy. Importantly, the approach gives no indication of the importance of government research activities in fostering agricultural growth. Nor does it provide information on whether or not the government is over or under-investing in the agricultural sector. However, for many African countries, the empirical evidence (Echeverria, 1990; Thirtle, Hadley & Townsend, 1995; Laker-Ojok, 1996; Van Zyl, Thirtle & Botha, 1997) shows that public sector research activities make important contributions to growth in agricultural productivity and that returns from investment in research were high (usually over 30%).

3. MEASURING AND EXPLAINING PRODUCTIVITY CHANGE: DATA AND METHODS

TFP indices are derived as the ratio of aggregate output to aggregate input. Of the three approaches frequently used in the productivity literature, the Malmquist productivity measure used here is based on the distance function and is advantageous since unlike the accounting and econometric measures, the Malmquist can be decomposed into efficiency and technical changes. It

does not require parametric (econometric) estimation of the technology nor does it require the behavioural assumptions of the econometric and index number approach. Importantly, it can be used to derive productivity measures even when price data is not available. For a detailed explanation of the methodology and calculations of the Malmquist index, interested readers are referred to Fare *et al* (1994), or Piesse *et al* (1996) for an application to South Africa.

Changes in the TFP index should be explained by the variables that shift the production function over time, as shown by Evenson *et al.* (1987). These determining variables are lagged R&D, extension expenditures, and farmer education. The weather is usually included to explain some of residual errors and several other explanatory variables such as farmer education can and have been used in the extensive literature in this area.

The output variable for wheat and maize is yields per hectare from the Ministry of Agriculture statistics for Tanzania. The conventional inputs used to derive the Malmquist TFP index are, labour (man days), fertiliser (tons), seeds (tons), chemicals (including herbicides and fungicides), in litres for the 1970-1999. The productivity measure is explained by the non-conventional inputs described below. The R&D expenditure is for both wheat and maize, for the 1970-1999 and is in constant 1970 Tanzania shillings, using the general price index as the deflator. The extension data is also in constant 1970 Tanzania shillings, deflated using the general price index.[1] The weather variable used is a weather dummy. All the determining variables except the weather may have a lagged effect on TFP, so the model becomes

$$TFP_t = \alpha + \sum_{i=0}^{n} \beta_i RD_{t-i} + \sum_{k=l}^{m} \delta_k EX_{t-k} + \phi W_t + \varepsilon_t \qquad (1)$$

where the TFP index at time t is a function of R&D expenditures lagged from one to n periods, the lagged effect of extension, W is current weather, and ε_t is the error or disturbance term. All the variables are in logarithms except the weather, so the coefficients may be interpreted as elasticities, ranging from zero to unity.

The numerous lagged values of R&D in (1) cause multi-collinearity and degrees of freedom problems. The normal escape route is to impose a second degree polynomial distributed lag structure (the inverted U-shape distribution), often with end point restrictions, to ensure that the lag coefficients (β_i) in (1) adopt a smooth and plausible distributed lag pattern. Though the approach is common in the literature (Doyle & Ridout, 1985 and Thirtle & Bottomley, 1988, 1989) the validity of the PDL and especially the end point restrictions have often been criticised (Madalla, 1977; Hatanaka & Wallace, 1980; Judge *et al*, 1988 and Hallam, 1990). These criticisms have been based on the notion that the PDL model may lead to biased estimates of the effect of research spending on productivity change.

To avoid the possibility of biased estimates, the less restrictive alternative proposed by Madalla (1977) and Hatanaka and Wallace (1980), which uses the lower order moments of the lag distribution, and applied by Silver and Wallace (1979) to estimate the lag relationship between wholesale and consumer prices is also used[2]. The approach has the advantage of not requiring a functional specification of the underlying distribution, and is thus of a less restrictive form, when compared to the PDL or other types of distributed lag models. Importantly, if the lag specification is of interest, it is also possible to use Pearson's method of equating moments (discussed below) to fit an appropriate lag structure to the data.

Following Hatanaka and Wallace (1980), and Silver and Wallace (1979) the transformation of the βs (lag coefficients of the R&D variable) in (1), into moments in matrix form is given by:

$$\mu = V\beta \tag{2}$$

where μ is the k+1 dimensional vector of moments, β the vector of the lag weights and V the bordered Vandermonde matrix. Since V is invertible, by substituting $V^{-1}\mu$ for β in (2) (in matrix form) gives:

$$TFP = XV^{-1}\mu + e = Z\mu + e \tag{3}$$

which can be estimated using ordinary least squares (OLS).

The μ's are the unadjusted moments in the non-normalised lag distribution, i.e., μ_0 is the zero ordered moment, μ_1 is the mean of the non-normalised lag distribution, etc. The moments around the mean can be estimated from the non-normalised moments by normalising β by the zero ordered moment

$$\beta_i^* = {}^{\beta_i}\!/_{\mu_0}.$$

The true moments are given by:

$$\begin{aligned} &M\mu_0 = u_0,\ M\mu_1 = {}^{\mu_1}\!/_{\mu_0},\ M\mu_2 = {}^{\mu_2}\!/_{\mu_0} - M_1^2,\ M\mu_3 = {}^{\mu_3}\!/_{\mu_0} - 3M_2M_1 - M_1^3, \\ &M\mu_4 = {}^{\mu_4}\!/_{\mu_0} - 4M_3M_1 - 6M_2M_1^{\ 2} - M_1^4 \end{aligned} \tag{4}$$

where $M\mu_0$ is the long-run effect, $M\mu_1$ is the mean, $M\mu_2$ is the variance, $M\mu3$, $M\mu4$ etc., of the normalised lag weights (Silver and Wallace, 1978). Following Silver and Wallace (1979), the first four adjusted moments given by (4) are used to derive Pearson's classification coefficient (*k*). This classification coefficient identifies the type of distribution that is appropriate to fit to the data.

The family of frequency functions f(x) which forms the basis of the Pearson distribution is given by:

$$\frac{df}{dx} = \frac{(x-a)f(x)}{b_0 + b_1x + b_2x^2} \tag{5}$$

where *a* and *b* are constants. From equation (5), *a* and *b* may be expressed in terms to the first four moments of the frequency function as shown by Kendall and Stuart (1987). The Pearson classification coefficient *k*, derived from the first four adjusted moments in equation (4) is given by (6):

$$k = \frac{\beta_1(\beta_2 + 3)^2}{4(2\beta_2 - 3\beta_1 - 6)(4\beta_2 - 3\beta_1)} \tag{6}$$

where

$$\beta_1 = {}^{Mu_3^2}\!/_{Mu_2^3},\ \beta_2 = {}^{Mu_4}\!/_{Mu_2^2}, \tag{7}$$

k distinguishes the types of Pearson distributions, and Table 1 below illustrates the main distribution classifications.

Overall, the derivation of the lag specification and curve fitting using the Pearson method involves the four step procedure set out below (see for example, Stuart and Ord, 1987, P217):

Step 1 Determine the first four moments, and β_1, β_2 from the data.

Table 1: Main curves in the Pearson distribution system

k	Type	Equation
k<0	I Beta distribution of the first kind	$f=\frac{1}{B(p,q)}x^{p-1}(1-x)^{q-1};\ 0\le x\le 1,\ p,q>0$
k>1	VI Beta distribution of the second kind	$f=\frac{1}{B(p,q)}\frac{x^{p-1}}{(1+x)^{p+q}};\ 0\le x\le\infty\ p,q>0,$ putting x = y/(1-y) reduces Type VI to the beta distribution of the first kind.
0<*k*<1	IV	$f=k\left(1+\frac{x^2}{a^2}\right)^{-m}\exp\left\{-v\ arc\ \tan\left(x/a\right)\right\},\ m>\frac{1}{2}$
k→∞	III (Gamma Distribution)	$f=\frac{1}{\Gamma(\lambda)}x^{\lambda-1}e^{-x},\ \lambda>0,\ 0\le x<\infty$ where $\Gamma(.)$ is the gamma function.

Step 2 Using β_1, β_2, determine Pearson's classification coefficient k, and hence the type of distribution.

Step 3 Equate the estimated moments to the moments of the estimated distribution and hence obtain the curve's parameters.

Step 4 Determine the fit of the distribution by solving the equation for the estimated parameters.

4. RESULTS: THE MALMQUIST TOTAL FACTOR PRODUCTIVITY INDEX

An aggregate Malmquist TFP index was constructed for maize and wheat for the 1970-1995 period. The productivity index was then decomposed into technical and efficiency changes over time. For the period as a whole, for the two crops, the average growth of productivity in the Malmquist index is 1.4%. The efficiency and technical change components show that on average the growth in the Malmquist productivity index was due solely to improvements in efficiency at 2.5% per annum, offset by technical regress at -1% per annum. Figure 1 shows that the Malmquist TFP index follows the path of technical regress more closely than it does the efficiency change component. As shown in Figure 1, the movements of both the technical and efficiency change components over the period appears to confirm the findings of Block (1994)

that agricultural productivity growth in African agriculture 1980s was due not to technical progress, but to macro-economic reforms and good weather.

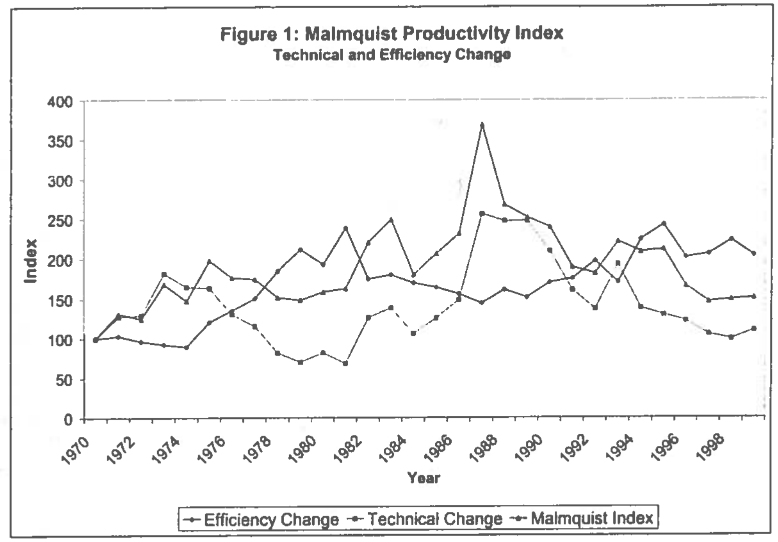

Figure 1: Malmquist productivity index

Indeed, the level of technical progress is lower in 1999, than its 1973 level, whereas the efficiency level at the end period (1999) is much higher than in the 1970s. The net effect is that TFP has been declining since reaching a peak in 1988 and this does seem to be correlated with the decline in R&D expenditures, with an appropriate lag.

5. EXPLAINING PRODUCTIVITY CHANGE: THE RETURNS TO R&D

From the unrestricted model given by equation (1), the Akaike Information Criteria (AIC) and the Schwartz Criteria (SC) are used to determine the lag length for the R&D and extension variables, by minimising the absolute value of the test statistic. The lag was found to be 10 years for the R&D variable, and a single lag of 3 years was required on the extension variable.

Keeping the 3 year lag on the extension variable, the Hatanaka and Wallace procedure is applied, as outlined above. The choice of the lag length implied by the data requires a search over the range of lag lengths where the estimated effects (moments) are relatively stable across estimates. Table 2 presents the first four adjusted lower order moments of the lag distribution (derived by applying (4)), for lag lengths of 5 to 10 years, where $M\mu_0$, $M\mu_1$, $M\mu_2$, $M\mu_3$, are the zero ordered moment, the means, variance, etc. Table 2 shows that the value of μ_0 rises with the longer lags, as does the standard errors (SE) (excluding the 10 year lag) and t-values. However the t-statistics of the μ_0 becomes significant only after the 6year lag.

Table 2: Non adjusted and adjusted lower order lag moment

Adjusted lag moments										
Lag	$M\mu_0=\mu_0\mu_0$	SE	t-stat	$M\mu_1$	$M\mu_2$	$M\mu_3$	$M\mu_4$	β_1	β_2	k
L5	0.04	0.07	0.57	-2.31	-4.99	-166.36	-2818.18	-222.13	-112.97	-7.21
L6	0.07	0.08	0.85	2.77	24.20	-53.99	444.33	0.21	0.76	-0.06
L7	0.11	0.08	1.48	4.87	25.51	-83.20	820.02	0.42	1.26	-0.11
L8	0.13	0.08	1.56	5.84	23.79	-110.09	1030.92	0.90	1.82	-0.23
L9	0.17	0.09	1.91	8.14	7.18	-38.42	409.22	3.99	7.94	-2.89
L10	0.24	0.06	4.17	10.40	-11.33	230.10	-3172.94	-36.38	-24.70	-7.74

Note: t-stat and SE are the calculated t values and standard errors for μ_0, respectively.

From Table 2, though the value of $M\mu_1$ rises with increasing lag lengths, those for $M\mu_2$, $M\mu_3$, and $M\mu_4$ rise and fall on both sides of the 9th lag, so this is the length chosen. Included in Table 2 are the betas β_1 and β_2, (see equation 7) from which the Pearson's coefficient classification k is derived (see equation 6). As shown in Table 2, the Pearson classification is less than unity for all the lag lengths considered, indicating a beta distribution, type I. The parameters for the beta distribution, and the curve fitting are derived by equating moments following Elderton and Johnson (1969) and Stuart and Ord (1987).

Figure 2 presents and compares the distributed lag structures for the R&D coefficients derived by fitting the beta distribution by solving moments, and those derived by imposing the second degree PDL, with both end constraints.

Though both distributions show a similar bell shaped lag structure, as can be seen from Figure 2, the beta distribution indicates a positive skew, rather than the symmetrical distribution of the PDL, with the peak effects of R&D occurring in the second and third year for the beta. The result is consistent with the peak effect of R&D on productivity in the unrestricted model. It is quite possible that this outcome may be indicative of the more adaptive nature of R&D in Tanzania. The PDL on the other hand peaks in the 5th year, declining thereafter.

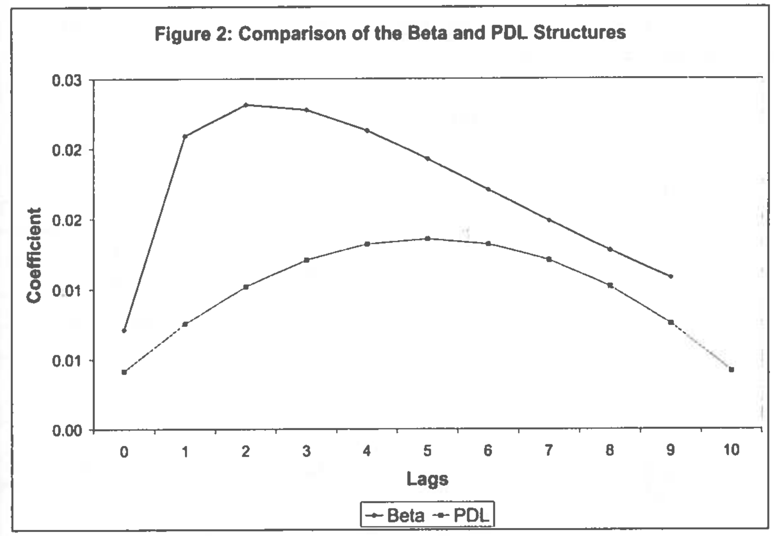

Figure 2: Comparison of the Beta and PDL structures

Table 3 presents the results for the three models, that is the unrestricted model, the PDL, and beta distribution. The sum of lag coefficients from the moments procedure and the unrestricted model are the same at 0.17%, and the result is slightly lower for the polynomial, at 0.11%. However, the range is not sufficiently large to have much affect on the ROR estimates that follow. Both the unrestricted and moments procedure indicate that the extension and weather variable are insignificant. But, in the PDL model both variables are significant. However, this outcome may be a result of any bias introduced in the model by the imposition of the PDL on the R&D variable. Overall, it does appear that the PDL, with both end points constrained, is just as good as the more flexible beta distribution. The Durbin-Watson indicates that the model is not serially correlated, but both models explain only a small part of the change in wheat and barley productivity. This is expected since other conditioning variables such as education are excluded from the model due to lack of availability.

The lag structures from the beta and PDL identify the effects of changes in R&D expenditures on the average productivity of wheat and maize.

Table 3: **Explaining productivity growth in Tanzania agriculture**

Variable	Coefficient	Std. Error	t-Statistic
Unrestricted Model			
Constant	3.63	0.33	9.71
Sum of the R&D Elasticities	0.17		
Extension Lagged 3 Years	0.09	0.07	1.14
Weather Index	0.16	0.13	1.19
PDL Model			
Constant	4.17	0.39	10.57
Sum of the R&D Elasticities	0.11	0.06	1.77
Extension Lagged 3 Years	0.07	0.04	1.90
Weather Index	0.15	0.10	1.53
Adjusted R^2	0.30		
Durbin Watson Statistic	1.20		
Beta Model			
Sum of the R&D Elasticities	0.17	0.09	1.91
Extension Lagged 3 Years	0.09	0.07	1.14
Weather Index	0.16	0.13	1.19
P	0.41	...	...
Q	6.89	...	...
Adjusted R^2	0.26		
Durbin Watson Statistic	1.64		

Note: P and Q are the distribution parameters of the fitted beta distribution.

Following the procedure outlined in Thirtle and Bottomley (1988) for calculating the ROR, the marginal internal ROR to public sector investment for maize and wheat combined is 57% using the PDL, and 64% from the beta distribution. These results do appear to confirm that the ROR to wheat and maize research in Tanzania is high, and is indicative of the importance of investing in R&D to increase crop productivity in Tanzania.

6. CONCLUSION

This paper presents evidence of crop level TFP growth in Tanzania for the first time. It calculates the Malmquist productivity measure for the period 1970-1999. The average productivity of wheat and maize increased at 1.4% per annum. The Malmquist index decomposes productivity change into its technical and efficiency change components and shows that whilst technical efficiency improved over the period at 2.5% per annum, technical regress at a rate of -1% per annum has had a negative effect on productivity change.

Explaining the change in the productivity of the crops by means of agricultural R&D, extension and weather shows that agricultural research spending has had a positive and significant impact on productivity change. Importantly, public sector R&D has contributed significantly to productivity growth, with an estimated ROR to research of 57-64%. This suggests that the recent reduction in R&D expenditures will have serious costs, in terms of declining TFP.

NOTES

1. *The yield data are from the Ministry of Agricultural Statistics in Tanzania, both the R&D and extension data are from the Ministry's Budget Reviews, Ministry of Agricultural Census.*

2. *Hallam (1990), Khatri (1994), and Amadi (2000) applied the moments procedure to UK agriculture.*

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