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Abstract

This paper examines changes in agricultural productivity in 18 developing countries over the period 1961–1985. We use a nonparametric, output-based Malmquist index and a parametric variable coefficients Cobb–Douglas production function to examine, whether our estimates confirm results from other studies that have indicated declining agricultural productivity in LDCs. The results confirm previous findings, indicating that at least half of these countries have experienced productivity declines in agriculture.

Keywords: Agricultural productivity

1. Introduction

In the economics literature, aggregate productivity refers to the amount of output obtained from given levels of inputs in an economy or a sector. It is an important topic of study, because productivity is one of the two fundamental sources of larger income streams; the other being savings, which permit more inputs to be employed. The analysis to follow examines productivity in the agricultural sectors of less developed countries (LDCs), where, contrary to the case of the developed world, productivity decline appears to have been widespread.

There is a substantial body of literature measuring multifactor agricultural productivity in the US (Ball, 1985; Jorgenson et al., 1987; Capalbo, 1988; Chavas and Cox, 1990; Burea et al., 1995; Trueblood and Ruttan, 1995). On the other hand, so far as we are aware, the only studies of multifactor agricultural productivity in LDCs are the ones by Fulginiti and Perrin (1993), Kawagoe et al. (1985), Lau and Yotopoulos (1989) and Kawagoe and Hayami (1985). Fulginiti and Perrin, examining essentially the same 1961–1985 LDC data set as in the present study, did not report direct measures of productivity change, but the results from their Cobb–Douglas production specification (reported in the present study) showed technological regression for 14 of the 18 countries. Kawagoe et al. (1985), using data for 1960, 1970 and 1980 in 21 developed countries (DCs) and 22 LDCs, estimated cross-country production functions with dummy variables for 1970 and 1980. They found technological regression during both decades for the LDCs, but technological progress in the DCs. Kawagoe and Hayami (1985) found similar results in that data set, using an indirect production function. Lau and Yotopoulos results also showed negative productivity for LDCs during the 1970s, but an increase during the 1960s.

Without exception, the studies of developed-country agriculture have shown substantial productivity

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increases, whereas the results for LDCs have consistently shown productivity declines, even in those LDCs where green revolution varieties of wheat and rice have been widely adopted. This discrepancy is surprising and puzzling. It is possible, as suggested elsewhere (Fulginiti and Perrin, 1993), that price policies or other interferences with the agricultural sector had a sufficiently chilling effect on incentives as to stifle potential productivity gains.

It is also possible that the methods and data previously used have inaccurately portrayed the LDCs agricultural sectors as regressing in productivity. Before explanations of the declining productivity phenomenon are pressed further, it is useful to examine the robustness of the result to alternative measurement techniques, and that is the purpose of the present study. We employ a parametric meta-production function and a non-parametric Malmquist index to examine the performance of the agricultural sectors in a set of 18 LDCs for which traditional indexing procedures are not feasible due to the lack of input prices.

2. Productivity measurement

Quantity-based conceptual approaches to measuring productivity change compare observed change in output with the imputed change in output that would have been possible from the observed input changes, the imputation being based on a production possibilities set estimated for the interval rather than prices as proxies for marginal product.

In this paper we use two quantity-based methods, a Malmquist index and a meta-production function. The Malmquist productivity index, following Färe et al. (1992) allows for the presence of technical inefficiencies and is nonparametric. The parametric production function approach assumes that, observed outputs are technically efficient. Neither requires the use of prices of inputs or outputs in its construction. The Malmquist index avoids specification bias but is deterministic while the production function is stochastic.

The Malmquist index is based on the output distance function defined as

$$D^T(x^t, y^t) \equiv \inf\left\{\theta : \left(x^t, \frac{1}{\theta}y^t\right) \epsilon\, S^T\right\} \quad (1)$$

where superscript T denotes the technology reference period, usually $T{=}t$ or $T{=}t{+}1$, S is the technology set, x^t is a vector of inputs and y^t is a vector of outputs used in year t. While, Caves et al. (1982) suggested the Malmquist index of change between year t and $t{+}1$ as the ratio $D^T(x^{t+1}, y^{t+1})/D^T(x^t, y^t)$, Färe et al. (1994) proposed to measure it as the geometric mean of these indexes for year t and $t{+}1$ reference technologies or

$$M(x^{t+1}, y^{t+1}, x^t, y^t) = \left[\frac{D^t(x^{t+1}, y^{t+1})}{D^t(x^t, y^t)}\frac{D^{t+1}(x^{t+1}, y^{t+1})}{D^{t+1}(x^t, y^t)}\right]^{1/2} \quad (2)$$

This expression can be factored into the product of technical change and efficiency change

$$M(x^{t+1}, y^{t+1}, x^t, y^t) = \frac{D^{t+1}(x^{t+1}, y^{t+1})}{D^t(x^t, y^t)}\left[\frac{D^t(x^{t+1}, y^{t+1})}{D^{t+1}(x^{t+1}, y^{t+1})}\frac{D^t(x^t, y^t)}{D^{t+1}(x^t, y^t)}\right]^{1/2} \quad (3)$$

The ratio outside the brackets measures the change in relative efficiency (i.e. the change in the distance of observed production from maximum feasible production) between years t and $t{+}1$, while the bracketed term measures the shift in technology (or technical change) between the two periods evaluated at x^t and x^{t+1}. A Malmquist index with value greater than unity reveals, improved productivity. Efficiency and technical change indices exceeding unity reflect gains in those components.

As an alternative to the nonparametric frontier Malmquist index, we estimated two production functions to measure total factor productivity. These are of the algebraic form

$$y(x:\beta) = A\prod_{i=1}^{n} x_i^{\beta i} \quad (4)$$

characterizing the maximum amount of scalar output y, which can be produced from any given set of conventionally measured inputs $x = (x_1, \ldots, x_n)$, where A and vector β designate all parameters. Let τ_k, $k = 1, 2, \ldots, m$ represent technology-changing variables that determine the production function parameters according to

$$\log A = \alpha_0 + \sum_{k=1}^{n} \alpha_k\tau_k + \mu_0,\; k = 1, \ldots, m \quad (4a)$$

$$\beta_i = \gamma_{i0} + \sum_{k=1}^{n} \gamma_{ik}\tau_k + \mu_i, \ i = 1, \ldots, n \qquad \text{(4b)}$$

where α's and γ's are fixed coefficients, μ_0 is a random variable distributed independently of the x_i's and τ_k's, and the μ_i's are random variables independent of the τ_k with mean zero and a finite positive semi-definite covariance matrix. Thus, the β_i's here represent a variable elasticity of output with respect to each of the input variables x. The technology-changing variables τ determine the production elasticities and are taken by the decision makers as parameters for the current production period. Expressing Eq. (4) in logarithms we obtain the convenient econometric model:

$$\log y = \alpha_0 + \sum_{k=1}^{n} \alpha_k \tau_k + \sum_{i=1}^{n} \gamma_{i0} \log x_i + \sum_{i=1}^{n}\sum_{k=1}^{n} \gamma_{ik}\tau_k \log x_i + \sum_{i=1}^{n} \mu_i \log x_i + \mu_0 \qquad (5)$$

Technology-changing variables of interest are those related to the quality of the natural and human resource endowments and those, that serve as incentives for innovation and adoption of new technology. A special case of this function which we also examine is the absence of technology-changing variables. In this case, Eq. (4) collapses to a Cobb–Douglas.

Using the production function approach we measure total factor productivity (TFP) as

$$\text{TFP} = \log(y_t/y_{t-1}) - \sum_{i=1}^{n} \beta_{it} \log(x_{it}/x_{it-1}) \qquad (6)$$

3. Data and results

This empirical study examines productivity changes in the agricultural sectors of 18 LDCs. This set of countries is of interest, because it includes a wide range of geographic locations, income levels and agricultural policies. A data set of consistently measured, quantity-based variables is available for these countries over the period 1961–1985 (Elisiana et al., 1993), but the lack of price data for inputs has precluded using Tornqvist-type indexes to examine productivity changes. The data consist of one output (y=1, aggregate agricultural output) and five inputs ($x = 1, \ldots, 5$; land, labor, fertilizer, machinery, and livestock). These are the same conceptual variables as used in the Hayami and Ruttan (1970) series of studies, though the present data include different estimates of several variables, a different set of countries, a longer time span, and annual observations.

For each successive pair of years, we evaluate each of the four distance functions required for the Malmquist index by solving a linear programming problem that imposes constant returns to scale. A total of 1512 such linear programming problems were solved. These solution values are used to calculate the Malmquist productivity change index, the efficiency change index, and the technical change index using Eq. (3) for each successive pair of years for each country (Fulginiti and Perrin, 1992, 1997).

Average Malmquist indexes and components are reported in Table 1. Argentina, Egypt and Korea were consistently Farrell-efficient, indicating that those three countries define the frontier of technology in the vicinity of their observed input mixes.

Notice from Table 1 that, two of these three frontier countries, Argentina and Korea, experienced declines in productivity during 1961–1985. This also means that the technological frontier in their vicinities was regressing. In Egypt, however, productivity and therefore the technological frontier in that vicinity advanced at the rate of 0.9% annually. Since, the countries defining the frontier declined in productivity on average, the average rate of technical change for the entire set of countries was −2.1% annually.

Average productivity performance (Malmquist indexes in the last row of Table 1) was a negative rate of −1.6% annually for the 1961–1985 period. Average productivity performance thus exceeded average technical change performance. If the frontier is everywhere regressing, improvements in a country's productivity will most likely be reflected as improvements in technical efficiency.

The country that had the best average rate of productivity gain was Turkey (2.3%), but gains were also recorded by six other countries as well (Chile, Dominican Republic, Egypt, Portugal, Malaysia and Sri Lanka).

To estimate the production function in Eq. (5), in addition to agricultural output and vector of five traditional inputs described above, a vector of technology changing variables is included

Table 1
Comparison of Malmquist and production function indexes of productivity change; 1961–1985

Country	Malmquist index	Technical change	Efficiency change	Prod. function var. coefficients	Prod. function fixed coefficients
Argentina	0.952	0.952	1.000	0.994	1.013
Brazil	0.995	0.984	1.011	0.973	1.002
Chile	1.011	0.997	1.014	1.008	1.014
Colombia	1.000	0.978	1.023	1.015	1.016
Dominican Rep.	1.010	0.973	1.033	0.989	1.004
Egypt	1.009	1.009	1.000	0.997	1.005
Ghana	0.951	0.976	0.974	0.992	0.975
Ivory Coast	0.934	0.943	0.991	0.986	0.983
Korea	0.925	0.925	1.000	0.957	0.964
Malaysia	1.004	0.992	1.012	0.984	1.004
Morocco	0.999	0.984	1.016	1.010	1.007
Pakistan	0.965	0.977	0.988	0.971	0.994
Philippines	0.997	0.981	1.016	1.001	1.018
Portugal	1.007	1.006	1.002	0.974	0.979
Sri Lanka	1.003	1.003	1.000	0.988	0.998
Thailand	0.938	0.964	0.973	0.963	0.999
Turkey	1.023	1.001	1.022	0.976	1.004
Zambia	0.999	0.976	1.024	0.977	0.986
Geometric ave.	0.984	0.979	1.005	0.986	0.998

($\tau = 1, 2, \ldots, 6$; land quality, agricultural research stock, primary school enrollment ratio, past output price, past wages, past fertilizer price). All countries and years are pooled together in a single equation of the form specified in Eq. (5). This pool gives a total of 410 observations, and the parameters are estimated with OLS. Although the error structure in Eq. (5) is assumed to be uncorrelated with the variables representing inputs, its variance is not. The Breusch and Pagan (1979) test for heteroskedastic errors indicated that the null hypothesis of homoscedasticity cannot be rejected at the 5% significance level. Table 2 presents, the parameter estimates of the model in Eq. (5). The table contains a total of 22 parameters, 12 of which are significant at the 1% level, 2 at the 5% level, and 2 at the 10% level. R^2 for the equation is 0.94 and collinearity diagnostics developed by Belsley et al. (1980) indicate an absence of multicollinearity. Total factor productivity is evaluated using Eq. (6) and the average by country is shown in the next to the last column of Table 1.

The last row of Table 2 contains the OLS estimated parameters of the fixed coefficients production function Eq. (4). Six parameters were estimated, five of them significant at the 1% level with the production elasticity for fertilizer being insignificant. R^2 is 0.84 and collinearity diagnostics indicate an absence of multicollinearity. In this case, the parameter estimates of the meta-production function are the production elasticities to use for all countries in evaluating total factor productivity by Eq. (6). These elasticity estimates, including the negative land elasticity, are similar to those of Evenson and Kislev (1975) and to those of Kawagoe et al. (1985) for their subset of LDCs. Lau and Yotopoulos hypothesized that a lack of country-specific effects is the explanation for negative land elasticity estimates from such models. Our variable coefficients model includes, country specific effects via the land quality and other technology-changing variables, and it yields higher estimates of land elasticity supporting the Lau–Yotopoulos hypothesis. The sum of production elasticities for the fixed coefficients production function yields 0.83 and that for the variable coefficients production function evaluated at the mean of the observations is 1.06, indicating constant returns to scale. The last column of Table 1 shows the productivity calculations using Eq. (6) for the fixed coefficients Cobb–Douglas. Even though these results are not inconsistent with the ones obtained by the other two methods, they will not be emphasized given the

Table 2
Least squares estimates of Eq. (3), 18 countries[a]

	Inputs					
	Land	Livestock	Machinery	Fertilizer	Labor	Intercept
Linear terms (γ_{i0})	0.040	0.146	0.173	0.093	0.838	−1.964
	(0.083)	(0.114)	(0.061)	(0.051)	(0.093)	(0.652)
Past output price (γ_{i1})	0.527	−0.554	0.064	−0.019	0.231	−2.266
	(0.044)	(0.054)	(0.030)	(0.024)	(0.048)	(0.336)
Past wages (γ_{i2})					−0.011	
					(0.003)	
Past fert. price (γ_{i3})				0.006		
				(0.006)		
Research (γ_{i4})	0.011	0.041	0.005	0.022	−0.140	0.523
	(0.016)	(0.022)	(0.013)	(0.009)	(0.017)	(0.119)
Land quality (γ_{i5})	0.054					
	(0.007)					
Schooling (γ_{i6})					0.040	
					(0.009)	
Fixed coefficients	−0.10	0.40	0.17	0.03	0.33	1.74
model	(0.027)	(0.036)	(0.022)	(0.021)	(0.028)	(0.218)

[a] Based on 410 observations during the years 1961–1985, standard errors in parentheses.

nature of the land production elasticity. We note that for 10 of the 18 countries, the fixed coefficients productivity estimates lie between the variable coefficients and the Malmquist index estimates.

Across countries, the fixed coefficients production function shows an average productivity decline of 0.2% annually, the variable coefficients production function measures a decline at an annual rate of 1.4% and the Malmquist index indicates a 1.6% rate of decline. On a country-by-country basis, the econometric approach reveals only Chile, Colombia, Morocco and Philippines with positive rates of productivity growth, whereas, the Malmquist approach measures eight positive rates. Two countries exhibited markedly worse Cobb–Douglas rankings as compared to Malmquist rankings (Portugal and Turkey), and two countries showed markedly better rankings (Argentina and Morocco). Where the two approaches indicated contrary directions of growth, however, the measured rates of change were very close to zero. Some of these differences could arise because of the shorter time periods included in the production function approach.

The econometric approach allows growth decomposition analysis. Table 3 shows the average annual growth rate of output, the imputed change in output that would have been possible from the observed input changes, and the Solow residual (technical change) for all countries. The table shows that on average the imputed change in output due to input change is more than the observed output change, giving a negative rate of technical change. It also shows that modern inputs, machinery and fertilizers, are big contributors to output growth. Half of the contribution is derived from machinery and 35% from fertilizers use, leaving only 15% of imputed output growth to changes in land, livestock and labor. This is consistent with the view that, green revolution technologies improve substitution possibilities in production allowing an optimal choice of technique that use nontraditional inputs more intensively. These figures highlight the importance of commercial inputs in measuring agricultural productivity in LDCs.

The most significant result of this comparison is that, agricultural productivity in these countries seems to have receded at an average rate of 1–2%, and this result is robust with respect to measurement techniques. It is perplexing, why these countries should have shown declining productivity and technological regression during the very period when green revolution seed varieties were spreading throughout many of these same countries. We have suggested some

Table 3
Average output change, input change, residual and growth accounting. Variable coefficients Cobb–Douglas production function

	Output change	Input change	Land	Livestock	Machinery	Fertilizer	Labor	Residual
Argentina	1.87	2.44	0.05	−0.11	0.54	2.00	−0.05	−0.57
Brazil	3.70	6.40	0.05	2.18	1.78	2.54	−0.26	−2.70
Chile	1.54	0.72	0.53	0.01	0.03	0.40	−0.23	0.82
Colombia	2.74	1.27	0.65	0.02	0.78	1.00	−0.85	1.47
Dominican Rep.	2.46	3.60	0.38	1.75	0.10	1.07	0.30	−1.14
Egypt	2.55	2.82	−0.01	0.75	0.84	1.18	0.06	−0.27
Ghana	0.52	1.32	0.09	0.05	0.63	0.35	0.19	−0.80
Ivory Coast	4.36	5.72	0.32	0.44	3.39	0.75	0.82	−1.36
Korea	3.82	8.11	0.01	0.07	7.55	0.56	−0.04	−4.29
Malaysia	3.13	4.71	0.56	−0.02	2.00	1.76	0.41	−1.58
Morocco	2.89	1.90	0.11	−0.66	1.21	1.45	0.23	0.98
Pakistan	3.68	6.55	0.08	1.23	2.54	2.91	0.11	−2.87
Philippines	3.70	3.51	0.12	0.43	1.39	1.47	0.08	0.19
Portugal	−0.73	1.82	−0.12	0.18	1.92	0.38	−0.53	−2.55
Sri Lanka	2.04	3.21	0.29	0.17	1.57	0.65	0.51	−1.17
Thailand	4.39	8.07	0.65	0.17	4.20	2.87	0.18	−3.68
Turkey	2.84	5.23	−0.03	0.05	2.53	2.71	−0.03	−2.39
Zambia	1.72	3.98	0.00	1.36	0.82	1.27	0.53	−2.26
Average	2.62	3.97	0.20	0.44	1.88	1.41	0.06	−1.34

answers in other studies. In examining the effects of price discrimination on agricultural productivity, one study suggested that, price-depressing policies reduce productivity with an elasticity of 0.13. In another study, we have shown that those countries with higher taxation show more regression than those with little or no taxation at all.

4. Conclusions

This paper examines changes in agricultural productivity in 18 LDCs over the period 1961–1985. The results confirmed previous findings that on average, agricultural productivity seems to have declined in these countries. This result was not uniform across countries. Chile and Colombia consistently show gains in productivity across the methods employed. Ghana, Ivory Coast, Zambia, Pakistan, Thailand and Korea shows productivity losses in all three approaches. The Malmquist index indicates that, productivity in frontier-establishing countries (Argentina and Korea) was declining, which resulted in a measured regression of technology (negative technological change) and a measured improvement in technical efficiency among most of the other countries. The econometric approach indicates that most output growth is imputed to commercial inputs like machinery and fertilizers.

We conclude that the phenomenon of negative productivity trends indicated by previous studies has not been an artifact of the analytical methods used, since the general results are now supported by a variety of methods. The diversity of performance across countries, however, opens the possibility of discovering what factors contribute to productivity improvement in these countries. In other studies, we did find that those countries that tax agriculture most heavily had, the most negative rates of productivity change, consistent with previous results suggesting that price policies may be one of the important contributing factor.

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