Developing Countries and Total Factor Productivity Growth in Agriculture: New Evidence Using a Malmquist Index with Constrained Implicit Shadow Prices

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1. Introduction

The importance of agricultural total factor productivity growth for developing countries has long been emphasized due to its determinant role in economic growth of low-income regions. The number of papers investigating cross country differences in agricultural productivity growth has expanded significantly in recent years and the Malmquist index has become extensively used in the measure and analysis of productivity after Färe, Grosskopf, Norris and Zhang (1994) showed that the index can be estimated using data envelopment analysis (DEA). This approach has been especially popular in the international comparison of agricultural productivity since it does not entail assumptions about economic behavior (profit maximization or cost minimization) and therefore does not require prices for its estimation which are normally not available.

Even though a priori price information is not needed, the DEA approach still uses implicit price information derived from the shape of the estimated production surface to estimate efficiency and non-parametric Malmquist indices. This implicit determination of shadow prices entails potential problems because these methods are susceptible to the effect of data noise and shadow prices can prove to be inconsistent with prior knowledge or accepted views on relative prices or cost shares. This is the case when linear programming problems used in DEA methods to estimate distance functions assign a zero or close to zero price to some factors because of the particular shape of the production possibility set. As a consequence, inputs considered important a priori could be all but ignored in the analysis, or could end up being dominated by inputs of secondary importance. Given the central role that implicit shadow prices play in non-parametric efficiency and TFP analyses it is remarkable that except for one exception (Coelli and Prasada Rao, 2003) none of the previous studies using non-parametric Malmquist indices in international comparisons of TFP growth, present the implicit shadow prices obtained in their analysis or discussed the implications of those prices in their results. None of the previous studies have attempted to control for this problem.

Given the importance of shadow prices in the estimation of the Malmquist TFP index, and the lack of attention paid to it in previous analysis, this paper contributes to the literature of international comparisons of agricultural TFP focusing on shadow prices and shares. First, as in Coelli and Prasada Rao (2003) we look at input and output shadow prices resulting from the linear programming problems used to estimate distance functions and check for the incidence of zero shadow prices in inputs. We find that even for the relatively large sample of countries in our study there is a high incidence of zero shadow prices in our estimates. Secondly, and given our findings, we introduce information on the likely values of input shadow shares of different countries and use this information to impose bounds to input shares in the LP programs used to estimate distance functions. In this way, we ensure that the most important outputs and inputs are included in the TFP estimation and that they are attached higher weights than the ones considered less important. Thirdly, and in order to see how different shadow prices affect the measure of TFP changes we estimate non-parametric Malmquist indices using unconstrained and constrained estimates of distance functions for 72 developing countries. Finally, we also present detailed results using constrained shadow prices of the contribution of efficiency and technical change to total TFP growth and the contribution of different countries and regions to total TFP growth in developing countries. We find that agricultural TFP in developing countries have been growing steadily in the past 20 years. Remarkably, we found a clear improvement in the performance of Sub-Saharan Africa since the mid 1980s.

The rest of the paper is organized as follows. Section 2 discusses methodological approaches to estimate distance functions and the Malmquist index. Section 3 deals with shadow prices and discusses the introduction of bounds to the values of input and output shadow share in the LP problems used to estimate distance functions. Section 4 compares efficiency and TFP results obtained with unconstrained and constrained LP problems. Section 5 discusses complete results of TFP growth and its components, efficiency and technical change, for 72 developing countries. The last section presents concluding comments.

2. Methodological Approach: Productivity Measure and Implicit Shadow Shares

Productivity change is defined as the ratio of change in output to change in input. In the hypothetical case of a production unit using one input to produce one output the measure of productivity is a simple task. However, production units use several inputs to produce one or more outputs, and under these circumstances the primary challenge in measuring TFP results from the need to aggregate the different inputs and outputs. The aggregation of inputs and outputs is both conceptually and empirically difficult.

Several methods to aggregate outputs and inputs are available resulting in different approaches to measuring TFP. These methods can be classified in four major groups: a) least-squares econometric production function models; b) total factor productivity indices; c) data envelop analysis (DEA); and d) stochastic frontiers (Coelli et al. 1998). The first two methods are normally used with times series data and assume that all production units are technically efficient. Methods c) and d) can be applied to a cross-section of firms, farms, regions or countries to compare their relative productivity. If panel data are available, production functions, DEA and stochastic frontiers can be used to measure both technical change and efficiency improvement.

The Malmquist index, pioneered by Caves, Christensen and Diewert (1982) and based on distance functions, has become extensively used in the measure and analysis of productivity after Färe, Grosskopf, Norris and Zhang (1994) showed that the index can be estimated using Data Envelope Analysis (DEA), a non-parametric approach. The non-parametric Malmquist index has been especially popular since it does not entail assumptions about economic behavior (profit maximization or cost minimization) and therefore does not require prices for its estimation. Also important is its ability to decompose productivity growth into two mutually exclusive and exhaustive components: changes in technical efficiency over time (catching-up) and shifts in technology over time (technical change).

To define the input-based Malmquist index it is necessary to characterize the production technology and production efficiency. We proceed to formally define technology and efficiency relating this measure with allocative efficiency and define the Malmquist index to measure TFP growth.

Technology and distance functions

We assume, as in Färe, Grosskopf, Norris and Roos (1998), that for each time period t = 1,…., T the production technology describes the possibilities for the transformation of inputs x^t into outputs y^t, or the set of output vectors **y** that can be produced with input vector **x**. The technology in period t with $y^t \in R_+^m$ outputs and $x^t \in R_+^n$ inputs is characterized by the production possibility set (PPS):

$$L^t = \{(y^t,x^t): \text{such that } x^t \text{ can produce } y^t\} \qquad (1)$$

The technology described by the set L^t satisfies the usual set of axioms: closedness; non-emptiness; scarcity; and no free lunch. The frontier of the PPS for a given output vector is defined as the input vector that cannot be decreased by a uniform factor without leaving the set. The input oriented distance function is defined at t as the minimum proportional contraction of input vector x^t given output y^t:

$$D_0^t(x^t, y^t) = \min \{\theta : (\theta x^t, y^t) \in L^t\} \qquad (2)$$

where θ is the coefficient multiplying x^t to get a frontier production vector at period t given y^t, and is equivalent to Farrell's technical efficiency[1]. This distance function in (2.2) can be calculated for the output and input vectors of decision making unit (DMU) 'o' (y_o,x_o) using DEA-like linear programming:

$$\min_{\theta,\lambda} \theta_o$$

s.t. (3)

$$\sum_{i=1}^{r} y_{ik}\lambda_i - y_{ok} \geq 0 \qquad \text{k} = 1,..,\text{m}$$

$$x_{ok}\theta - \sum_{i=1}^{r} x_{ij}\lambda_i \geq 0 \qquad \text{j} = 1,...,\text{n}$$

$$\lambda \geq 0$$

where i represents the r different DMUs that define the PPS. What this problem does is to maximize the contraction of the input vector of country 'o' while still remaining within the feasible input set. The efficiency score obtained (θ_o) will take values between

[1] For convenience and as is frequently assumed in the literature, the input distance function defined here is equal to the inverse of the input distance function defined by Shephard (1970).

0 and 1 with 1 indicating that the firm is at the frontier (input vector cannot be contracted without that observation leaving the feasible set).

Problem (3) is known as the envelope form of the DEA approach. An equivalent dual approach can be derived from the envelope or primal form (see Kousmanen et al., 2004). The envelope approach is normally preferred to estimate distance and efficiency because it requires fewer constraints than the dual form. On the other hand, the dual form has the advantage of a more intuitive specification, offering also an economic interpretation of the problem.

The dual linear program measures efficiency as the ratio of a weighted sum of all outputs over a weighted sum of all inputs. The weights are obtained solving the following problem (Coelli and Prasada Rao, 2001):

$$\max_{p,w} \sum_{k=1}^{m} p_k y_{ik} \Big/ \sum_{j=1}^{n} w_j x_{ij}$$

$$\text{s.t.} \qquad (4)$$

$$\sum_{k=1}^{m} p_k y_{ik} \Big/ \sum_{j=1}^{n} w_j x_{ij} \le 1 \qquad \mathrm{i} = 1,\ldots,\mathrm{r}$$

$$p_k, w_j \ge 0 \qquad \mathrm{k} = 1,\ldots,\mathrm{m};\ \mathrm{j} = 1,\ldots,\mathrm{n}$$

Problem (4) clearly shows the intuition behind this approach to measure efficiency but cannot be used as such because it has an infinite number of solutions. In order to solve this problem we normalize the ratio by imposing: $\sum_{j=1}^{n} w_j x_{ij} = 1$ (Coelli and Prasada Rao, 2001). With this new constraint, the dual problem becomes (with p and w different from ρ and ω):

$$\max_{\rho,\omega} \sum_{k=1}^{\mathrm{m}} \rho_{\mathrm{k}} y_{ik}$$

$$s.t.$$

$$\sum_{j=1}^{n} \omega_j x_{ij} = 1 \qquad (5)$$

$$\sum_{k=1}^{m} \rho_k y_{ik_i} - \sum_{j=1}^{n} \omega_j x_{ij} \le 0 \qquad \mathrm{i} = 1,\ldots,\mathrm{r}$$

$$\rho_k, \omega_j \ge 0 \qquad \mathrm{k} = 1,\ldots,\mathrm{m};\ \mathrm{j} = 1,\ldots,\mathrm{n}$$

Kuosmanen et al. (2004) generalize the dual interpretation of the distance function to the case of closed, non-empty production sets satisfying scarcity and no free lunch showing that the distance (2.2) has the equivalent dual formulation:

$$D_0^t(x^t, y^t) = \max\left\{\frac{\rho y^t}{\omega x^t} : \frac{\rho y^t}{\omega x^t} \leq 1 \forall (y^t, x^t) \in L^t\right\} \quad (6)$$

They interpret this distance function as "the return to the dollar[2], at the "most favorable" prices, subject to a normalizing condition that no feasible input-output vector yields a return to the dollar higher than unity at those prices." The optimal weights ρ_k and ω_j are respectively output k and input j shadow prices with respect to technology L^t. There exists a vector of shadow prices for any arbitrary input-output vector, however, these prices not need to be unique. Kuosmanen et al. (2004) define the set of shadow price vectors as:

$$V^t(y^t, x^t) = \left\{(\rho, \omega) \in R_+^{n+m} : \frac{\rho y}{\omega x} = D^t(y, x); \frac{\rho y^t}{\omega x^t} \leq 1 \forall (y^t, x^t) \in L^t\right\} \quad (7)$$

Kousmanen et al. (2004) contend in the spirit of the theory of revealed preferences (Varian, 1984), that "the observed allocation of inputs and outputs can indirectly reveal the economic prices underlying the production decision". Based on this, they assume that DMUs allocate inputs and outputs to maximize return to the dollar. These prices are well defined and are observed by decision makers but are not known by the productivity analyst. Assuming that DMUs allocate inputs and outputs to maximize return to the dollar, Kousmanen et al. (2004) define that the production vector (y^t,x^t) is allocatively efficient with respect to technology L and prices (ρ^t, ω^t) iff $(\rho^t, \omega^t) \in V^t(y^t,x^t)$. Allocative efficiency is a necessary but not sufficient condition for maximization of return to the dollar given that allows for technical inefficiency (production in the interior of the PPS). This dual approach to the problem of efficiency and input allocation will be used later in this study to analyze the plausibility of shadow prices obtained when

[2] Return to the dollar is an economic criterion to evaluate performance and measures the ability of producers to attain maximum revenue to cost introduced by Georgescu-Roegen (1951). The assumption of allocative efficiency depends on the specified economic objectives of the firms through the shadow price domain (Kousmanen et al., 2004).

estimating efficiency and eventually to correct those prices introducing exogenous information to the LP problem.

The Malmquist TFP index

The Malmquist index measures the TFP change between two data points (e.g. those of a country in two different time periods) by calculating the ratio of the distance of each data point relative to a common technological frontier. Following Färe et al. (1994), the Malmquist index between period t and t+1 is given by:

$$M_o = \left[M_o^t \times M_o^{t+1}\right]^{1/2} = \left[\frac{D_o^t(x^{t+1}, y^{t+1})}{D_o^t(x^t, y^t)} \times \frac{D_o^{t+1}(x^{t+1}, y^{t+1})}{D_o^{t+1}(x^t, y^t)}\right]^{1/2} \quad (8)$$

This index is estimated as the geometric mean of two Malmquist indices, one using as a reference the technology frontier in t and a second index that uses frontier in t+1 as the reference.

Färe, Grosskopf, Norris, and Zhang (1994) showed that the Färe index could be decomposed into an efficiency change component and a technical change component, and that these results applied to the different period-based Malmquist indices.

$$M_o = \frac{D_o^{t+1}(x^{t+1}, y^{t+1})}{D_o^t(x^t, y^t)} \times \left[\frac{D_o^t(x^{t+1}, y^{t+1})}{D_o^{t+1}(x^{t+1}, y^{t+1})} * \frac{D_o^t(x^t, y^t)}{D_o^{t+1}(x^t, y^t)}\right]^{1/2} \quad (9)$$

The ratio outside the square brackets measures the change in technical efficiency between period t and t+1. The expression inside brackets measures technical change as the geometric mean of the shift in the technological frontier between t and t+1 evaluated using frontier at t and at t+1 respectively as the reference. The efficiency change component of the Malmquist indices measures the change in how far observed production is from maximum potential production between period t and t+1 and the technical change component captures the shift of technology between the two periods. A value of the efficiency change component of the Malmquist index greater than one means that the production unit is closer to the frontier in period t+1 than it was in period t: the production unit is catching-up to the frontier. A value less than one indicates efficiency regress. The same range of values is valid for the technical change component of total productivity growth, meaning technical progress when the value is greater than one and technical regress when the index is less than one. The method has been extensively applied to the international comparison of agricultural productivity. See for example: Bureau et al. (1995), Fulginiti and Perrin (1997), Lusigi and Thirtle (1997), Rao and Coelli (1998), Arnade (1998), Fulginiti and Perrin (1999), Chavas (2001), Suhariyanto et al. (2001), Suhariyanto and Thirtle (2001), Trueblood and Coggins (2003), Nin et al. (2003a), Nin et al. (2003b), Nin et al. (2007), and Ludena et al. (2007).

To estimate TFP growth in Sub-Saharan Africa, the only internationally comparable data base available to us is that of the Food and Agriculture Organization of the United Nations (FAO). It provides national time series data from 1961-2003 for the total quantity of different inputs and output volumes measured in international dollars. One output (agricultural production) and five inputs (labor, land, fertilizer, tractors and animal stock) for 106 countries, including 29 Sub-Saharan African (SSA) countries, 21 Latin American, 13 Asian and 11 Middle Eastern and North African (MENA) countries are used to estimate agricultural TFP. Agricultural output is expressed as the quantity of agricultural production measured in millions of 1999-2001 "international dollars". Agricultural land is measured as the number of hectares of arable and permanent cropland; labor is measured as the total economically active agricultural population; fertilizer is metric tons of nitrogen, potash, and phosphates used measured in nutrient-equivalent terms; livestock is the total number of animal heads (cattle, buffalos, sheep, goats, pigs and laying hens) measured in cow equivalents.

The PPS defined by the output-input vector of these 106 countries is checked in the next section for the presence of outliers. This analysis allows us to drop some of the extreme points in the PPS to obtain the final set of observations that will be used in the estimate of the Malmquist index.

3. Constraining Implicit Input Shares in DEA Analysis

The lack of prior price information for inputs was pointed out in section 2 as the prime motivation for estimating non-parametric Malmquist indices for the analysis of TFP change in developing countries. As is the case with other TFP indices, the non-parametric Malmquist index is specified as the ratio of the weighted sum of outputs to the weighted sum of inputs of a specific DMU. In contrast with other methods, this index doesn't require a priori information on prices as it is defined using distance functions which are conveniently determined through linear programming.

Even though a priori price information is not needed, the DEA procedure still uses prices to estimate efficiency and non-parametric Malmquist indices. When solved, these linear programming programs define a set of weights for the inputs and outputs that minimize the distance of each assessed DMU to the technological frontier (maximize its efficiency). These weights can be interpreted as implicit shadow prices, and if the choices of input-output bundles made by each DMU are guided by rational economic objectives, these shadow prices then reveal the underlying economic prices (opportunity costs) which are unknown to the researcher (Kuosmanen et al. 2006). The principle of these approaches is to "let the data speak for themselves rather than to enforce them to some rigid, arbitrarily specified functional form," which is important when no a priori information about the technology is available.

Without constraining the linear programming problem used in DEA to determine efficiency, we allow total flexibility in choosing shadow prices. Because of the lack of information about prices mentioned above, in most of the literature on efficiency and non-parametric TFP analysis, flexibility has been considered to be one of the major advantages of DEA when comparing it with other techniques used to measure efficiency or productivity (Pedraja-Chaparro, 1997). However, total flexibility for the weights has been criticized on several grounds, given that the weights estimated by DEA can prove to be inconsistent with prior knowledge or accepted views on relative prices or cost shares. Pedraja-Chaparro et al. (1997) stress two main problems related with allowing total shadow price flexibility. First, by allowing total flexibility in choosing shadow prices, inputs considered important a priori could be all but ignored in the analysis, or could end up being dominated by inputs of secondary importance. This is the case when because of the particular shape of the PPS, linear programming problems assign a zero or close to zero price to some factors. Second, the relative importance attached to the different inputs and outputs by each unit should differ greatly. Although some degree of flexibility on the weights may be desirable for the DMUs to reflect their particular circumstances, it may often be unacceptable that the weights should vary substantially from one DMU to another. Another argument used against total flexibility of shadow prices (Kuosmanen et al. 2006) is that in some cases, a certain amount of information regarding the inputs and outputs prices or shares might be available. In that case, the analysis can be strengthened by imposing price information in the form of additional constraints that define a feasible range for the relative prices.

Figure 1. Production possibility space and the occurrence of zero shadow prices

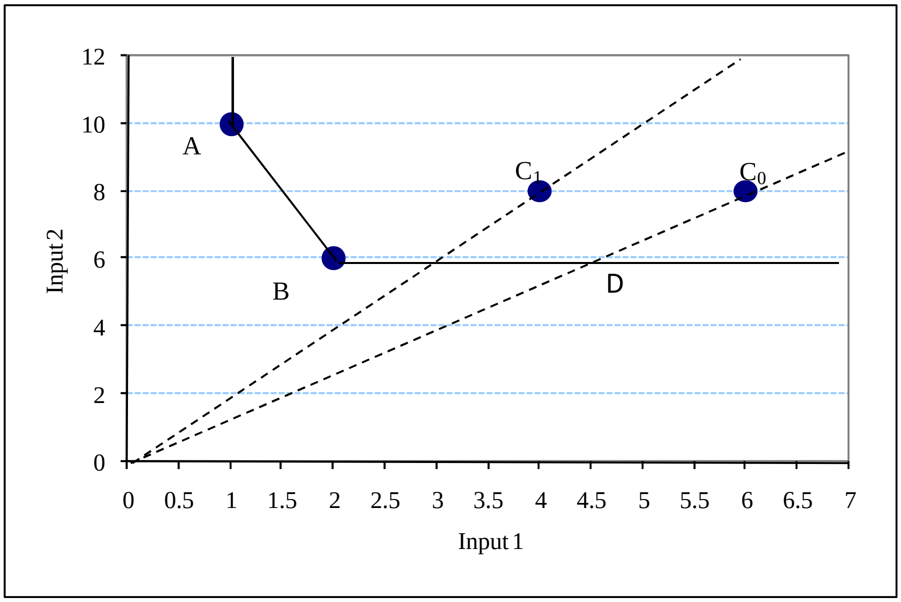


Figure 1 shows graphically, as in Coelli and Prasada Rao (2001), how zero shadow prices occur and how they can affect TFP measures. The figure represents three DUMs producing one unit of output with different levels of inputs. Production units A and B are efficient units defining the frontier while C_0 is inefficient. C_0's distance to the frontier can be defined as: $OD/OC_0<1$. However, point D is not an efficient point given that B produces the same output with less input 1 than D. In terms of the LP problem (3) this means that the constraint for input 1 is not binding for DMU C_0:

$$x_{C_0k}\theta - \sum_{i=1}^{r} x_{ij}\lambda_i > 0 \qquad j=1 \tag{10}$$

A non binding constraint for input 1 in problem (3) means a zero shadow price for input 1 in the dual problem (5). With zero shadow prices for input 1, input substitution is not defined. What happens if production unit improves efficiency reducing the amount of input 1 needed to produce one unit of output (moving from C_0 to C_1)? This horizontal move, parallel to line AD results in no change in efficiency, that is: OD/OC_0 =

$OD/OC_1<1$. In the dual problem, a reduction of input 1 will have no effect on productivity given that its shadow price is zero, which means that only input 2 is considered for estimating efficiency. We refer the reader to Coelli and Prasada Rao (2001) to see how the implied value shares used in DEA estimates of TFP affected the results in a number of studies using this methodology.

Therefore, it seems to be a strong case for the analysis of shadow prices obtained from DEA when estimating efficiency and TFP, and eventually for considering the introduction of restrictions on shadow prices or cost shares, setting limits between which prices or shares can vary. Allen et al. (1997) and Pedraja-Chaparro et al. (1997) are surveys that review the evolution, development and research directions on the use of restrictions to shadow prices in DEA analysis and how the flexibility to choose those prices might be restricted. More recent papers have contributed to this research area improving on the problem of zero weights. See for example: Silva Portella and Thanassoulis (2006); Thanassoulis and Allen (1998); and Allen and Thanassoulis, (2004). As noted by Kuosmanen et al. (2006), most of this literature focuses mainly on technical rather than economic issues, incorporating restrictions under the label of "weight restrictions" or "assurance regions" with no reference to the alternative interpretation of the weights as economic prices or marginal substitution or transformation rates between inputs or between outputs.

Given the central role that implicit shadow prices play in non-parametric efficiency and TFP analyses (see Coelli and Prasada Rao, 2001), it is remarkable that except for one exception (Coelli and Prasada Rao, 2003) none of the previous studies using non-parametric Malmquist indices referred to in section 2, present the implicit shadow prices obtained in their analysis or discussed the implications of those prices in their results. In what follows we focus on the shadow shares obtained for developing countries when estimating efficiency in order to see the importance assigned to different inputs in the analysis and the magnitude of the problem of zero prices. We then discuss the introduction of constraints on shadow prices.

In order to define suitable limits to the value that input shares take, we set an upper and a lower bound (a_i,b_i) to the input share in problem 5. We define as in section 2 the standard distance function where ρ and ω are respectively the output and input shadow prices and $\omega_i^t \times x_{io}^t$ (the input shadow prices multiplied by the input quantities) is equal to the implicit input shares as shown in Coelli and Prasada Rao (2001),

$$D^t(y_k^t, x_k^t) = \underset{\rho,\omega}{Max} \sum_{r=1}^{s} \rho_r y_{ro}^t$$

s.t. (11)

$$\sum_{i=1}^{m} \omega_i^t x_{io}^t = 1$$
$$\sum_{r=1}^{s} \rho_r^t y_{rj}^t - \sum_{i=1}^{m} \omega_i x_{ij}^t \leq 0$$
$$a_{io}^t \leq \omega_i^t x_{io}^t \leq b_{io}^t \quad \mathrm{i} = 1,\ldots,\mathrm{m}$$
$$\rho, \omega \geq 0$$

Note that the introduction of bounds on shadow input shares constitutes additional constraints to the original formulation. Restricted and unrestricted models will provide the same results only if all the additional restrictions imposed are non-binding. In general, the narrower the bounds imposed, the larger the expected differences between the outcomes of each model.

In order to define the bounds for the input shares we introduce information on the likely value of the shares of the different inputs from Evenson and Dias Avila (2007). In that paper, the authors estimate crop input cost shares for 78 developing countries by adjusting carefully measured share calculations for India using input/cropland quantity ratios of these developing countries. Given that inputs used in this study are similar to those used here, we use information the shares estimated by Evenson and Dias Avila to determine the maximum and minimum share values for each input among all countries and use these estimated shares as a rough reference to set the limits between which input shares in DEA estimates for developing countries can vary. By setting these general limits for all countries we allow input shares to vary keeping flexibility and uncertainty about the true value of these shares and contemplating differences in circumstances of the individual countries. With the imposition of share bounds, the LP program can no longer disregard the less favorable inputs and we ensure that the most important outputs and inputs are attached higher weights than the ones considered less important.

Table 1. Bounds of input shares used in LP programs to estimate distance functions

	SSA	Latin America	South Asia	East & Southeast Asia	North Africa & Middle East
Lower bound					
Land	0.32	0.12	0.33	0.36	0.26
Labor	0.25	0.31	0.15	0.29	0.31
Tractors	0.00	0.00	0.00	0.00	0.07
Animal Stock	0.07	0.03	0.04	0.02	0.02
Fertilizer	0.00	0.00	0.00	0.00	0.01
Upper bound					
Land	0.72	0.36	0.72	0.66	0.58
Labor	0.52	0.70	0.50	0.49	0.46
Tractors	0.10	0.23	0.13	0.17	0.20
Animal Stock	0.32	0.19	0.27	0.10	0.10
Fertilizer	0.10	0.34	0.20	0.22	0.08

Table 1 above shows bounds of input shares derived from estimates by Evenson and Dias Avila (2007) for developing countries. According to these estimates, land has the largest shares in most regions, with bounds between 0.32-0.72 in SSA and South Asia, 0.33 and 0.66 in East & Southeast Asia and 0.26-0.58 in NAME. The share of land in Latin America is lower than for other regions in Evenson's and Dias Avila's results (0.12-0.36). Labor follows land in terms of its share with a minimum lower bound of 0.25 in SSA and a maximum upper bound of 0.70 in Latin America. Fertilizer and tractor shares vary between 0.0001 and 0.34 and 0.0001 and 0.23 respectively. Upper and lower bounds for animal stock are 0.32 and 0.02 respectively. Looking at the lower bound values, land is the most important input for SSA, South Asia and East and Southeast Asia (0.32-0.36). On the other hand, Latin America has labor with a higher share than land. MENA shows values between those in SSA and Latin America. The upper bounds show that we expect Latin America and SEA to show higher shares of fertilizer and tractors. It is important to notice that there is a strong interdependence between the bounds on different weights given that setting an upper bound on one input weight imposes a lower bound on the total virtual input of the remaining inputs.

Average input shares for developing countries resulting from estimations of efficiency using LP are shown in table 2. Results show that major differences in input shares happen in SSA and MENA. On average, the differences between constrained and unconstrained estimated shares are not big, as shown by the results for all countries with the major differences in labor and animal stocks. However, results differ between regions. Shadow shares for Latin America, South Asia and East and Southeast Asia are close to the ones expected from Evenson and Dias Avila's estimates. The major differences occur with estimates in SSA and MENA. In the case of SSA, the unconstrained results show very low values for labor and land, and relatively high values for animal stock, tractors and fertilizer. For MENA countries, unconstrained results give animal stock the largest share (almost 0.5) with values of labor and land of 0.17 and 0.11 respectively. After introducing constraints to input shares, land share in SSA increases from 0.18 to 0.39. Similarly, labor share increases from 0.08 in the unconstrained case to 0.30 in the constrained problem. Fertilizer and tractor shares reduced from 0.15 and 0.26 to 0.09 and 0.05 respectively. In the case of MENA, animal stock's share reduces from 0.48 to 0.10.

The input share values shown in table 2 are calculated as the simple average of the individual country input shares in different periods. What these averages don't show is the number of zero values of different input shares in different countries when no bounds are imposes to estimate shares. We present unconstrained shadow shares for individual countries in table 3, while figure 2 shows the incidence of zero input prices. Considering average values for the period 1964-2003 for all countries, we find that 26 percent of countries show zero shadow prices for land. The number of countries showing zero shadow prices for labor and animal stock in the same period is also high (24 percent in the case of stock and 19 percent land). The percentage of countries with zero fertilizer and tractor shadow prices is much lower (9-11 percent respectively).

Table 2. Average input shares from unconstrained and constrained estimations of efficiency

	Land	Labor	Tractors	Animal stock	Fertilizer	Total
Unconstrained						
All	0.31	0.22	0.17	0.19	0.10	1.00
Sub-Saharan Africa	0.18	0.08	0.26	0.33	0.15	1.00
Central America (a)	0.30	0.24	0.22	0.13	0.10	1.00
South America	0.32	0.27	0.22	0.07	0.11	1.00
South Asia (b)	0.53	0.06	0.17	0.11	0.12	1.00
East & Southeast Asia	0.37	0.14	0.15	0.19	0.15	1.00
Middle East & N.Africa	0.11	0.17	0.10	0.47	0.15	1.00
Constrained						
All	0.35	0.33	0.13	0.11	0.08	1.00
Sub-Saharan Africa	0.39	0.30	0.09	0.17	0.05	1.00
Central America	0.25	0.38	0.19	0.10	0.08	1.00
South America	0.27	0.37	0.18	0.07	0.11	1.00
South Asia	0.53	0.16	0.12	0.06	0.13	1.00
East & Southeast Asia	0.40	0.30	0.12	0.06	0.11	1.00
Middle East & N.Africa	0.32	0.37	0.15	0.10	0.06	1.00
Absolute difference						
All	0.04	0.11	0.04	0.08	0.03	0.29
Sub-Saharan Africa	0.21	0.23	0.17	0.16	0.10	0.87
Central America	0.05	0.13	0.03	0.04	0.02	0.26
South America	0.04	0.09	0.04	0.00	0.01	0.19
South Asia	0.01	0.09	0.05	0.05	0.00	0.20
East & Southeast Asia	0.03	0.16	0.03	0.12	0.04	0.38
Middle East & N.Africa	0.21	0.20	0.05	0.37	0.08	0.91
Total	0.59	1.01	0.41	0.82	0.28	

Notes: a) Includes Mexico. b) Lower bound for labor was relaxed, allowing lower values than measures in Evenson and Dias Avila (2007)

At the country level, table 3 shows Asian countries like Bangladesh, China, Indonesia, Vietnam, and Nepal, and African countries like Botswana, Guinea, Mozambique and Tanzania with zero or closed to zero shadow prices for labor. Several African countries also show shadow shares for land close to zero (Algeria, Libya, Syria, Tunisia, Cameroon, Chad, Gabon, Lesotho, Nigeria, South Africa, Sudan, Togo and Zambia). In Latin America, only two Caribbean countries (Jamaica and Trinidad & Tobago) show low shadow shares for labor and only Mexico, Honduras and Nicaragua appear with a shadow share for land below 0.10.

Table 3 Unconstrained shadow prices from DEA estimates of distance functions

	Labor	Land	Fertilizer	Tractors	Animal Stock
Costa Rica	0.15	0.54	0.10	0.14	0.08
Dominican Rep.	0.24	0.19	0.07	0.33	0.17
El Salvador	0.20	0.38	0.14	0.19	0.10
Guatemala	0.18	0.27	0.13	0.26	0.15
Haiti	0.23	0.50	0.05	0.19	0.03
Honduras	0.32	0.06	0.05	0.29	0.29
Jamaica	0.08	0.57	0.22	0.09	0.04
Mexico	0.32	0.09	0.09	0.33	0.17
Nicaragua	0.62	0.02	0.05	0.22	0.08
Panama	0.29	0.32	0.07	0.29	0.03
Trinidad & Tobago	0.06	0.41	0.17	0.06	0.30
Argentina	0.46	0.12	0.11	0.15	0.16
Bolivia	0.24	0.27	0.16	0.34	0.00
Brazil	0.36	0.29	0.08	0.27	0.00
Chile	0.29	0.15	0.13	0.09	0.33
Colombia	0.18	0.52	0.08	0.19	0.02
Ecuador	0.42	0.18	0.06	0.26	0.08
Paraguay	0.27	0.42	0.14	0.17	0.01
Peru	0.12	0.44	0.09	0.24	0.11
Uruguay	0.15	0.55	0.17	0.12	0.02
Venezuela	0.25	0.23	0.11	0.41	0.00
Bangladesh	0.00	0.68	0.12	0.21	0.00
India	0.15	0.39	0.14	0.21	0.11
Nepal	0.00	0.76	0.10	0.13	0.01
Pakistan	0.13	0.18	0.07	0.18	0.43
Sri Lanka	0.04	0.63	0.19	0.13	0.01
China	0.00	0.60	0.19	0.17	0.04
Indonesia	0.08	0.46	0.15	0.16	0.15
Laos	0.04	0.72	0.16	0.07	0.01
Malaysia	0.34	0.00	0.08	0.24	0.34
Mongolia	0.26	0.02	0.13	0.04	0.54
Philippines	0.22	0.30	0.15	0.21	0.13
Thailand	0.22	0.26	0.11	0.17	0.24
Vietnam	0.00	0.57	0.23	0.16	0.04

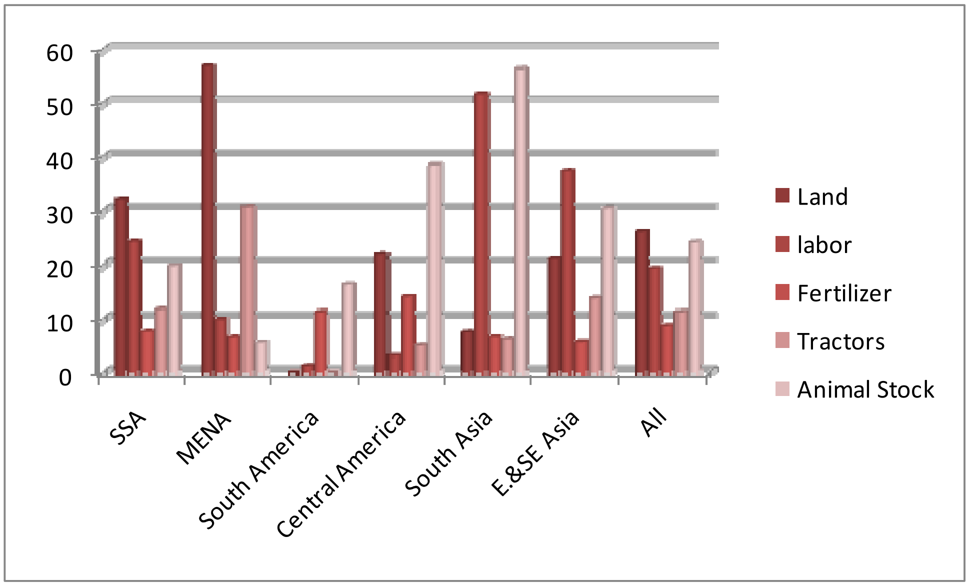
Table 3 (continued) Unconstrained shadow prices from DEA estimates of distance functions

	Labor	Land	Fertilizer	Tractors	Animal Stock
Algeria	0.16	0.02	0.20	0.03	0.60
Egypt	0.08	0.53	0.10	0.08	0.21
Iran	0.20	0.09	0.12	0.17	0.42
Jordan	0.12	0.23	0.15	0.08	0.42
Libya	0.28	0.00	0.20	0.10	0.42
Morocco	0.22	0.00	0.12	0.27	0.39
Syria	0.18	0.03	0.10	0.08	0.62
Tunisia	0.22	0.00	0.17	0.04	0.58
Turkey	0.12	0.12	0.17	0.04	0.55
Benin	0.36	0.39	0.05	0.16	0.03
Botswana	0.04	0.60	0.05	0.02	0.29
Burkina Faso	0.28	0.34	0.06	0.22	0.10
Cameroon	0.56	0.00	0.04	0.16	0.25
Chad	0.61	0.00	0.02	0.15	0.21
Ethiopia	0.31	0.40	0.04	0.12	0.12
Gabon	0.55	0.01	0.08	0.05	0.31
Gambia	0.13	0.55	0.04	0.24	0.04
Ghana	0.16	0.38	0.09	0.23	0.13
Guinea	0.04	0.65	0.06	0.13	0.12
Guinea-Bissau	0.43	0.39	0.04	0.14	0.00
Ivory Coast	0.35	0.15	0.06	0.22	0.22
Kenya	0.12	0.41	0.08	0.16	0.23
Lesotho	0.18	0.08	0.10	0.16	0.48
Madagascar	0.24	0.44	0.07	0.15	0.09
Malawi	0.01	0.51	0.08	0.17	0.23
Mali	0.24	0.41	0.05	0.11	0.19
Mauritania	0.23	0.30	0.04	0.12	0.31
Mozambique	0.00	0.37	0.10	0.10	0.43
Nigeria	0.51	0.08	0.06	0.19	0.17
S. Africa	0.21	0.04	0.24	0.20	0.31
Senegal	0.37	0.35	0.04	0.17	0.07
Sierra Leone	0.06	0.55	0.06	0.15	0.19
Sudan	0.31	0.00	0.03	0.27	0.40
Swaziland	0.10	0.67	0.15	0.07	0.01
Tanzania	0.00	0.79	0.11	0.10	0.00
Togo	0.67	0.01	0.07	0.14	0.12
Zambia	0.38	0.00	0.06	0.31	0.26
Zimbabwe	0.09	0.43	0.15	0.13	0.20

The incidence of zero shadow prices also shows variation across regions. Asian countries show high incidence of zero prices in animal stock and labor. SSA countries show relatively large number of zero shadow prices in land and labor, while in MENA 56 percent of all countries show zero shadow prices for land. In the case of Central America, 38 percent of all countries have zero shadow prices for animal stock. The incidence of zero shadow prices is the lowest in South America where shadow price of animal stock is zero in only 16 percent of all countries, with lower figures for other inputs.

These results show that with unconstrained shadow prices, agricultural efficiency and productivity changes are measured without bringing into consideration the use of land in almost 60 percent of all MENA countries, in one third of SSA countries and in one fourth of other regions. Also, labor is given a zero share in estimates of productivity in half of the Asian countries and animal stock is not included in half of South Asian countries, 40 percent of Central American countries and 30 percent of other Asian countries. The incidence of zero shadow prices of relevant inputs justifies the introduction of constraints to shadow prices in order to ensure that all relevant inputs are included in the estimation of efficiency and productivity indices.

Figure 2. Percentage of countries showing zero shadow prices in an average year



In order to see how different shadow prices affect the measure of TFP changes we estimate non-parametric Malmquist indices using unconstrained and constrained distance functions for the 72 developing countries in our sample. Results are presented in table 4. On average for the period 1964-2003, the absolute difference between unconstrained and constrained TFP growth rates is 0.33 percentage points with average growth rates of 0.75 and 0.60 with constrained and unconstrained shadow prices respectively.

At the individual country level, most countries showing large absolute differences between both estimates are MENA and SSA countries. This can be seen in figure 3, showing the average absolute difference for different groups of countries. In the case of MENA countries, the average absolute difference between the two estimated average growth rates is 0.64, while for SSA countries this value is 0.35. Differences between estimates in Asian and Latin American countries are smaller and around 0.25 in all cases.

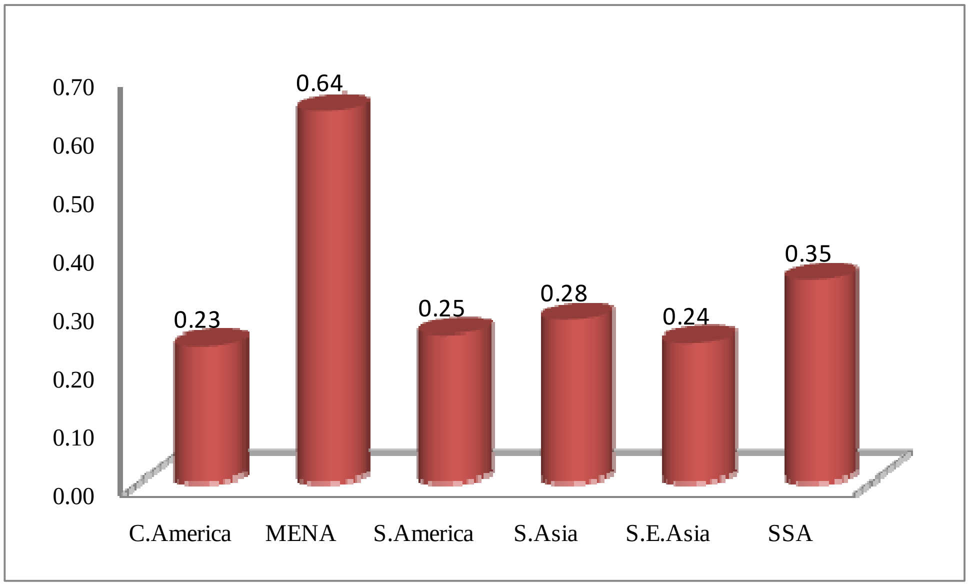
Table 4 Average TFP growth 1964-2003 estimated using constrained and unconstrained shadow prices

Country	Constrained	Unconstrained	Difference	Abs.diff.
Libya	2.11	3.28	-1.17	1.17
Burkina Faso	-1.29	-0.43	-0.86	0.86
Algeria	0.44	1.17	-0.73	0.73
Iran	0.42	1.08	-0.67	0.67
Syria	0.44	0.81	-0.37	0.37
Tunisia	1.56	1.91	-0.35	0.35
Botswana	-0.63	-0.28	-0.35	0.35
Togo	-0.40	-0.10	-0.30	0.30
Chile	1.85	2.10	-0.26	0.26
Venezuela	1.54	1.76	-0.22	0.22
Zimbabwe	0.28	0.50	-0.22	0.22
Jamaica	0.82	1.02	-0.20	0.20
Zambia	0.11	0.29	-0.17	0.17
Guatemala	0.97	1.10	-0.13	0.13
Brazil	1.40	1.49	-0.08	0.08
Morocco	0.90	0.98	-0.08	0.08
Peru	1.16	1.22	-0.06	0.06
Cameroon	0.05	0.10	-0.05	0.05
Ethiopia	-0.41	-0.37	-0.04	0.04
India	-0.36	-0.32	-0.04	0.04
El Salvador	0.82	0.85	-0.03	0.03
Philippines	1.08	1.11	-0.03	0.03
Mexico	1.19	1.22	-0.03	0.03
China	0.95	0.97	-0.03	0.03
Dominican Rep.	1.68	1.68	-0.01	0.01
Lesotho	-1.68	-1.68	0.00	0.00
Mali	0.45	0.41	0.04	0.04
Sri Lanka	0.72	0.67	0.05	0.05
Guinea-Bissau	-0.17	-0.22	0.05	0.05
Senegal	-1.00	-1.06	0.06	0.06
Mozambique	-0.33	-0.40	0.06	0.06
Bolivia	0.56	0.50	0.07	0.07
Vietnam	-0.21	-0.28	0.07	0.07
Tanzania	0.72	0.65	0.07	0.07
Swaziland	0.37	0.28	0.09	0.09
Chad	-0.27	-0.36	0.09	0.09

Table 4 (continued) Average TFP growth 1964-2003 estimated using constrained and unconstrained shadow prices

Country	Constrained	Unconstrained	Difference	Abs.diff.
Sudan	-0.17	-0.26	0.10	0.10
Malaysia	1.90	1.79	0.10	0.10
Ecuador	0.53	0.39	0.13	0.13
Kenya	1.71	1.53	0.17	0.17
Honduras	1.68	1.50	0.18	0.18
Gambia	-1.29	-1.50	0.21	0.21
Nepal	0.68	0.45	0.23	0.23
Panama	0.19	-0.04	0.23	0.23
Madagascar	-0.16	-0.40	0.23	0.23
Colombia	2.73	2.49	0.23	0.23
S. Africa	1.60	1.35	0.25	0.25
Pakistan	0.12	-0.14	0.26	0.26
Benin	2.02	1.75	0.27	0.27
Turkey	0.77	0.48	0.28	0.28
Costa Rica	3.72	3.43	0.29	0.29
Guinea	-0.08	-0.39	0.31	0.31
Uruguay	0.82	0.48	0.34	0.34
Malawi	0.58	0.24	0.34	0.34
Laos	0.94	0.59	0.35	0.35
Nicaragua	0.87	0.52	0.35	0.35
Indonesia	0.49	0.14	0.35	0.35
Egypt	2.08	1.72	0.36	0.36
Trinidad.&Tobago	1.96	1.58	0.38	0.38
Thailand	0.12	-0.37	0.49	0.49
Mongolia	-0.04	-0.53	0.49	0.49
Paraguay	0.79	0.22	0.56	0.56
Argentina	2.88	2.30	0.58	0.58
Haiti	0.36	-0.37	0.73	0.73
Ghana	1.10	0.36	0.75	0.75
Bangladesh	0.60	-0.22	0.82	0.82
Sierra Leone	0.97	0.12	0.84	0.84
Nigeria	0.72	-0.23	0.95	0.95
Gabon	1.87	0.89	0.98	0.98
Ivory Coast	1.12	0.07	1.05	1.05
Mauritania	1.46	0.33	1.13	1.13
Jordan	2.71	0.98	1.74	1.74
Average	0.44	0.60	-0.16	0.20

Figure 3 Average absolute difference between TFP growth rates estimated using constrained and unconstrained shadow prices for different regions.



We conclude that the incidence of zero and "unusual" shadow prices can have a big effect on TFP measures using DEA methods. Even though we use a large sample of more than a hundred countries to define the PPS used to estimate distance functions using DEA methods, we still find a high incidence of zero shadow prices. This incidence is higher in African countries which appear to differ from other countries in the sample in terms of their combination of inputs and outputs. In the case of SSA countries, unconstrained distance estimates give high shares to tractors and fertilizers, not considering land and labor in TFP growth estimates in many of these countries. These results confirm the importance of reporting shadow prices in DEA estimates of Malmquist indices as discussed in Coelli and Prasada Rao (2003), but also show the need to adjust shadow input shares to reflect the relative importance of the different inputs according to a priori available information on these shares. The next section presents complete results of TFP growth and its components for our sample of developing countries using constrained shadow prices as discussed in this section.

4. TFP Growth and Agricultural Performance in Developing Countries, 1964-2003

The performance of the agricultural sector in developing countries measured as growth in TFP in the past 40 years was poor. A weighted average of growth in the 72 countries considered in this study indicates that agricultural productivity grew for this group of countries at an annual rate of 0.58 percent. This means that agricultural productivity in developing countries in 2003 was only 26 percent bigger than it was in 1964. This poor performance however hides great variability across regions, countries and time. Two main periods with contrasting performances in developing countries' TFP growth can be distinguished. During 1964-1983, agricultural TFP growth was negative (-0.48) and recovers in 1984-2003 with an average growth rate of 1.65 percent during this period.

Figure 4 shows the evolution of the weighted average of cumulative agricultural TFP growth in developing counties and its decomposition in technical change and efficiency. The recovery in the last 20 years can be explained in terms of improved efficiency, with acceleration in technical change in the last ten years. Figure 5 shows trends in cumulative TFP growth (weighted averages) for different groups of developing countries.

Figure 4 Cumulative agricultural TFP growth in developing countries 1964-2003 (weighted average, index in 1964=1)

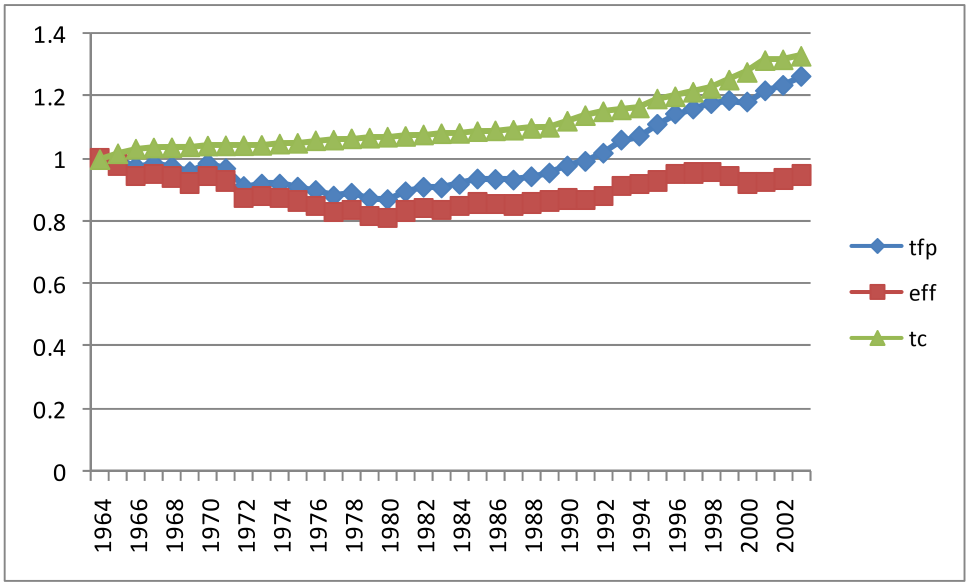
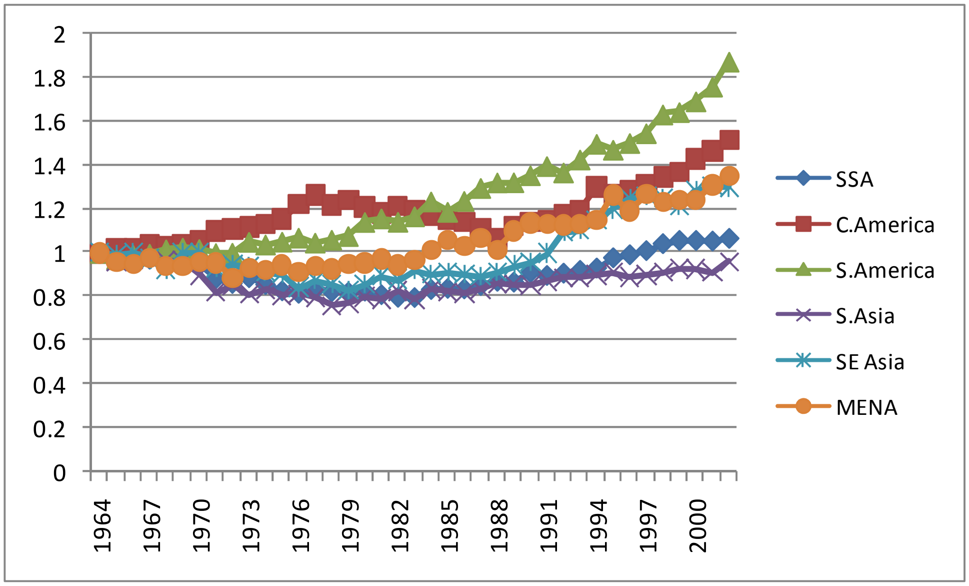


Figure 5 Cumulative agricultural TFP growth in different developing regions 1964-2003 (weighted average, index in 1964=1)



Latin America shows the best performance with sustained TFP growth since the late 1970s in South America and strong growth since the late 1980s Mexico and Central America. MENA and SE Asia also show a strong performance since the late 1980s. Sub-Saharan Africa shows a clear recovery since 1985 after several years of declining TFP. South Asia still appears as the less dynamic region with growth lagging behind Sub-Saharan Africa.

Table 5 presents average TFP growth and decomposition for all countries in our sample, for the second half of the period considered here, the years of improved performance in TFP growth in most developing countries. Twenty countries increased TFP at an average rate above two percent and 13 countries show negative growth rates. Most growth in SSA is explained by efficiency gains, with several countries catching-up after several years of negative growth. On the other hand, several Latin American and MENA countries show significant growth in technical change.

Table 5 Mean technical efficiency change, technical change and TFP change, 1984-2003

	TFP	Efficiency	Technical change
Costa Rica	3.95	0.72	3.21
Dominican Rep.	1.83	0.00	1.83
El Salvador	1.91	0.88	1.02
Guatemala	1.37	0.98	0.39
Haiti	-0.95	-1.09	0.14
Honduras	4.47	3.79	0.65
Jamaica	0.59	-0.60	1.19
Mexico	0.83	-0.02	0.84
Nicaragua	1.19	0.77	0.41
Panama	-0.01	-0.58	0.57
Trinidad & Tobago	3.55	1.48	2.04
Argentina	1.97	0.17	1.80
Bolivia	2.84	2.84	0.00
Brazil	2.95	1.67	1.26
Chile	3.18	1.26	1.90
Colombia	3.52	1.08	2.41
Ecuador	1.80	1.19	0.60
Paraguay	-0.10	-0.33	0.23
Peru	2.55	1.85	0.69
Uruguay	-0.56	-1.54	0.99
Venezuela	1.45	-0.04	1.49
Bangladesh	0.86	0.86	0.00
India	0.60	-0.30	0.91
Nepal	1.56	1.17	0.38
Pakistan	1.72	0.05	1.66
Sri Lanka	-0.40	-0.54	0.14
China	2.55	1.30	1.23
Indonesia	-0.65	-0.77	0.12
Laos	2.12	1.77	0.34
Malaysia	2.29	1.73	0.56
Mongolia	-0.25	-0.56	0.31
Philippines	1.37	1.19	0.18
Thailand	-0.37	-0.77	0.40
Vietnam	0.27	-0.47	0.75

Table 5 (continued) Mean technical efficiency change, technical change and TFP change, 1984-2003

	TFP	Efficiency	Tech.change
Algeria	3.51	2.33	1.15
Egypt	2.58	0.00	2.58
Iran	2.51	1.33	1.16
Jordan	1.96	0.07	1.89
Libya	2.95	1.30	1.62
Morocco	2.66	1.47	1.17
Syria	0.84	-0.12	0.96
Tunisia	2.62	1.65	0.96
Turkey	1.46	0.73	0.72
Benin	3.50	1.86	1.61
Botswana	-0.69	-0.78	0.09
Burkina Faso	1.22	1.15	0.07
Cameroon	1.63	1.40	0.22
Chad	1.19	0.95	0.23
Ivory Coast	0.99	0.87	0.13
Ethiopia	0.59	0.56	0.03
Gabon	1.72	0.56	1.15
Gambia	-1.09	-1.09	0.00
Ghana	4.10	4.10	0.00
Guinea	0.09	0.07	0.02
Guinea-Bissau	0.94	0.94	0.00
Kenya	1.57	1.14	0.42
Lesotho	-2.17	-2.93	0.79
Madagascar	0.32	0.32	0.00
Malawi	1.45	1.37	0.07
Mali	0.53	0.42	0.12
Mauritania	-0.18	-0.21	0.03
Mozambique	0.91	0.90	0.01
Nigeria	2.30	2.29	0.01
Senegal	0.69	0.56	0.13
Sierra Leone	1.29	1.20	0.09
South Africa	1.76	0.61	1.15
Sudan	0.85	0.79	0.06
Swaziland	-0.03	-1.35	1.33
Tanzania	1.68	1.66	0.01
Togo	1.74	1.26	0.48
Zambia	1.56	0.97	0.58
Zimbabwe	0.75	-0.36	1.12

5. Conclusions

In this paper we analyze input shadow prices determined by the linear programming problems used to estimate distance functions and the evolution of agricultural TFP growth in developing countries in the past 40 years using a non-parametric Malmquist index and its components: efficiency and technical change. The analysis is conducted using available internationally comparable data of the Food and Agriculture Organization of the United Nations (FAO) for the period 1961-2003. One output (agricultural production) and five inputs (labor, land, fertilizer, tractors and animal stock) for 98 countries, including 74 developing countries are used to estimate TFP.

We find that even for the relatively large sample of countries in our study, there is a high incidence of zero shadow prices in our estimates. In order to define suitable limits to the value that input shares take, we set bounds to the input shares determined by shadow prices in the DEA problem. In order to define these bounds we introduce information on the likely value of the shares of the different inputs from Evenson and Dias Avila (2007). Using this information we are able to determine maximum and minimum share values for each input among all countries while keeping flexibility and uncertainty about the true value of these shares. With the imposition of share bounds in the LP programs, we ensure that the most important outputs and inputs are included in the TFP estimation and that they are attached higher weights than the ones considered less important.

Taking the average year of the period 1964-2003, we find that 26 percent of developing countries show zero shadow prices for land, while 24 percent of the countries also show zero shadow prices for animal stock. The number of countries showing zero shadow prices for labor is also high (19 percent). The percentage of countries with zero fertilizer and tractor shadow prices is much lower (9-11 percent respectively). These averages hide a large variability between countries. In Sub-Saharan Africa, 32 percent of countries show zero shadow prices for land with many countries showing also zero shadow prices for labor and animal stock (24 percent in the case of labor and 20 percent in animal stock). This means that the standard procedure to estimate the Malmquist index results in measures of TFP growth that don’t include land or labor as inputs in almost 25 percent of developing countries and in one third of SSA countries. The incidence of zero shadow prices of relevant inputs justifies the introduction of constraints to shadow prices in order to ensure that all relevant inputs are included in the estimation of efficiency and productivity indices.

In order to see how different shadow prices affect the measure of TFP changes we estimate non-parametric Malmquist indices using unconstrained and constrained estimates of distance functions for 72 developing countries. Annual agricultural productivity growth measured with constrained shadow prices is 0.74 percent, higher than growth obtained with unconstrained input shares (0.57 percent). At the individual country level, results between annual TFP growth rates estimated with constrained and unconstrained input shares differ significantly, in particular in Sub-Saharan Africa, North Africa and the Middle East. For instance, annual productivity growth in Libya with unconstrained shadow prices is 3.28 percent on average for the period 1964-2003. In this case, unconstrained shadow prices mean that land is not included as an input in the estimation of TFP. When land is included, annual TFP reduces to 2.11 percent for the same period. Several Sub-Saharan African countries also show significant differences between constrained and unconstrained results. Annual TFP growth estimated for Ivory Coast is 0.07 percent with unconstrained shadow prices and 1.12 percent with constrained when all inputs are considered. Overall, 26 percent of the countries in our sample show a difference in the annual TFP growth rate of more than 50 percent of the unconstrained growth rate when shares are constrained for the estimation of the Malmquist index.

The paper also presents detailed results using constrained shadow prices of the contribution of efficiency and technical change to total TFP growth and the contribution of different countries and regions to total TFP growth in developing countries. We find that agricultural TFP in developing countries have been growing steadily in the past 20 years. Remarkably, we found a clear improvement in the performance of Sub-Saharan Africa since the mid 1980s.

References

Allen, R., A.D. Athanassopoulos, R.G. Dyson and E. Thanassoulis, 1997. "Weight Restrictions and Value Judgements in DEA: Evolution, Development and Future Directions, Annals of Operations Research 73: 13-34

Allen, R.C. and W.E. Diewert, 1981 "Direct Versus Implicit Superlative Index Number Formulae." Review of Economics and Statistics 63: 430-435

Allen and Thanassoulis, 2004. "Improving envelopment in data envelopment analysis." European Journal of Operational Research, 154(2): 363-379

Arnade, C., 1998. "Using a Programming Approach to Measure International Agricultural Efficiency and Productivity", Journal of Agricultural Economics, 49: 67-84.

Bureau, C., R. Fare and S. Grosskopf, 1995. "A Comparison of Three Nonparametric Measures of Productivity Growth in European and United States Agriculture", Journal of Agricultural Economics, 45, pp. 309-326.

Caves, D.W., Christenesen, L. R. and Diewert, W. E., 1982. "The economic theory of index numbers and the measurement of input, output and productivity." Econometrica 50, 1393--1414.

Chavas, J.P., 2001. "An International Analysis of Agricultural Productivity", In L. Zepeda, ed., Agricultural Investment and Productivity in Developing Countries, FAO, Rome.

Coelli, T.J. and D. S. Prasada Rao, 2005 "Total factor productivity growth in agriculture: a Malmquist index analysis of 93 countries, 1980-2000." Agricultural Economics, 2005, 32, (s1), 115-134

Coelli, T.J. and D.S. Prasada Rao, 2001. Implicit Value Shares in Malmquist TFP Index Numbers. Centre for Efficiency and Productivity Analysis (CEPA). Working Papers No. 4/2001. School of Economic Studies, University of New England, Armidale.

Coelli, T.J., D.S. Prasada Rao and G.E. Battese, 1998, An Introduction to Efficiency and Productivity Analysis. Kluwer academic Publishers, Boston.

Evenson, R.E. and A. F. Dias Avila, 2007. FAO Data-Based TFP Measures
In: Chapter 31 Vol. 3 Handbook of Agricultural Economics: Agricultural Development: Farmers, Farm Production and Farm Markets, Eds: R.E. Evenson, P. Pingali and T.P. Schultz, Elsevier.

FAO (Food and Agriculture Organization of the United Nations), 2007. FAOSTAT database. http://www.fao.org/. Accessed May 5.

Färe, R., Grosskopf, S., Norris, M. and Zhang, Z., 1994. "Productivity growth, technical progress and efficiency change in industrialized countries." American Economic Review 84, 66--83.

Färe, R., Grosskopf, S., Norris, M. and Roos, P., 1998. "Malmquist productivity indexes: a survey of theory and practice." In: Färe, R., Grosskopf, S. and Russell, R. (Eds.), Index Numbers: Essays in Honour of Sten Malmquist, Kluwer Academic Publishers, Boston/London/Dordrecht, pp. 127--190.

Farrel, M., 1957. "The Measurement of Productive Efficiency,: Journal of the Royal Statistical Society. Series A, general, 120(3): 253-281.

Fulginiti, L., and R.K. Perrin, 1997. "LDC Agriculture: Nonparameric Malmquist Productivity Indexes", Journal of Development Economics, 53: pp. 373-390.

Fulginiti, L., and R.K. Perrin, 1999. "Have Price Policies Damaged LDC Agricultural Productivity?", Contemporary Economic Policy, 17: 469-475.

Fulginiti, L.E., R.K. Perrin, and B.Yu, 2004 "Institutions and Agricultural Productivity in Sub-Saharan Africa". Agricultural Economics. Vol. 4: 169– 180.

Georgescu-Roegen, N., 1951. "The Aggregate Linear Producion Function and its Application to von Newmans's Economic Model." In; T. Koopmans (ed.) Acivity analysis of Production and Allocation. Wiley, New York.

Griliches, Z., 1987. "Productivity: Measurement Problems." In: J. Eatwell, M. Milgate and P. Newman (eds.). The New Palgrave: A Dictionary of Economics. New York; Plagrave Macmillan

Kuosmanen, T., L. Cherchye and T. Sipiläinen, 2006. "The law of one price in data envelopment analysis: Restricting weight flexibility across firms," European Journal of Operational Research, 127(3): 735-757

Kuosmanen, T., T. Post and T. Sipiläinen, 2004. "Shadow Price Approach to total Factor Productivity Measurement: With an Applicatioin to Finnish Grass-Silage Production." Journal of Productivity Analysis, 22, 95-121

Ludena, C.E. , T. W. Hertel, P. V. Preckel, K. Foster, and A. Nin, 2007. "Productivity Growth and Convergence in Crop, Ruminant and Non-Ruminant Production: Measurement and Forecasts". Agricultural Economics 37(1): 1-17

Lusigi, A.and C. Thirtle, 1997. "Total Factor Productivity and the Effects of R&D in African Agriculture", Journal of International Development, 9: 529-538

Nin, A., C. Arndt and P. Preckel, 2003a: “Is Agricultural Productivity in Developing Countries Really Shrinking? New Evidence Using a Modified Non-Parametric Approach.” Journal of Development Economics 71: 395-415.

Nin, A., C. Arndt, T. Hertel, and P. Preckel, 2003b. “Bridging the Gap Between Partial and Total Factor Productivity Measures Using Directional Distance Functions.” American Journal of Agricultural Economics 85(4): 937-951.

Nin, A., B. Yu, and S. Fan, 2007. “The Dragon and the Elephant: Why Have Agricultural Productivity Growth in China and India Differed?” Paper presented at the International Agricultural Productivity Growth Workshop, Economic Research Service USDA, March 15.

Rao, D.S.P. and T.J. Coelli, 1998. “Cathc-up and Convergence in Global Agricultural Productivity, 1980-1995”, CEPA Working Papers, No. 4/98, Department of Econometrics, University of New England, Armidale, pp 25.

Pedraja-Chaparro, F., J. Salinas-Jimenez, and P. Smith, 1997. “On the Role of Weight Restrictions in Data Envelopment Analysis, Journal of Productivity Analysis 8: 215-230

Shephard, R., 1970, Theory of Cost and Production Functions. New Jersey: Princeton University Press.

Silva Portella, M.C. and E. Thanassoulis, 2006, “Zero Weights and Non-zero Slacks: Different Solutions to the Same Problem.” Annals of Operational Research, 145:129-147

Suhirayanto, K., A. Lusigi and C. Thirtle, 2001. “Productivity Growth and Convergence in Asian and African Agriculture”, in Asia and Africa in comparative Econommic Perspective, P. Lawrence and C. Thirtle, eds. London: Palgrave, 258-274.

Suhirayanto, K., and C. Thirtle, 2001. “Asian Agricultural Productivity and Convergence”, Journal of Agricultural Economics, 52:96-110.

Thanassoulis, E. and R. Allen, 1998. “Simulating Weights Restrictions in Data Envelopment Analysis by Means of Unobserved DMUs.” Management Science, 44(4): 586-594

Trueblood, M.A. and J. Coggins, 2003. “Intercountry Agricultural Efficiency and Productivity: A Malmquist Index Approach”, mimeo, World Bank, Washington D.C.

Varian, H. 1984. “The Nonparametric Approach to Production Anaylsis.” Econometrica 52(3): 579-597

Winters, P., A. de Janvry, E. Sadoulet and K. Stamoulis, 1998. The Role of Agriculture in Economic Development: Visible and Invisible Surplus Transfers. Journal of Development Studies 34(5): 71-97