# Getting Implicit Shadow Prices Right for the Estimation of the Malmquist Index: The Case of Agricultural Total Factor Productivity in Developing Countries


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# ABSTRACT

The Malmquist index has become extensively used in international comparisons of agricultural productivity since it does not require prices for its estimation, which are normally not available. However, the DEA approach used to estimate this index still uses implicit price information. This 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 on cost shares. In this paper we analyze implicit input shadow shares used in the DEA approach to estimate agricultural productivity using the Malmquist index for 72 developing countries. We then set bounds to the implicit input shares introducing information on their likely value and compare constrained and unconstrained input shares. We conclude that the incidence of zero shadow prices justifies the introduction of constraints in the estimation of the Malmquist index. The paper also presents detailed results of TFP growth in developing countries using constrained shadow shares for their estimation. We find that agricultural TFP has been growing steadily in the past 20 years even if countries like China, Brazil and India are not considered. Remarkably, we find a clear improvement in the performance of Sub-Saharan Africa since the mid 1980s.



Key words: Malmquist, shadow prices, total factor productivity

JEL Codes: D2

# Getting Implicit Shadow Prices Right for the Estimation of the Malmquist Index: The Case of Agricultural Total Factor Productivity in Developing Countries

Alejandro Nin-Pratt and Bingxin Yu

## 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 et al. (1994) showed that the index can be estimated using data envelopment analysis (DEA). This approach has been especially popular in international comparisons 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 production surface that allows the estimation of efficiency measures 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, 2005), to our knowledge none of the previous studies using non-parametric Malmquist indices in international comparisons of TFP growth discussed the implications of shadow prices in their results, nor had attempted to control for the problem of "unexpected" shadow prices.

This paper contributes to the literature of international comparisons of agricultural TFP focusing on shadow prices and shares. Our goal is to determine the incidence of zero shadow input prices in the standard estimation of the non-parametric Malmquist index and present a modify procedure that introduces *a priori* information on the expected values of shadow input shares.[1]

The rest of the paper is organized as follows. Section 2 discusses methodological approaches to estimate distance functions and the Malmquist index. Section 3 discusses the introduction of bounds to input shadow shares. Section 4 compares TFP results obtained with unconstrained and constrained LP problems. Section 5 presents results of TFP growth for 72 developing countries. The last section concludes.

[1] This same procedure could be used to constraint output shares. In this paper however, we only deal with input shadow prices and work with only one output to simplify the analysis and facilitate the presentation of results

## 2. METHODOLOGICAL APPROACH: PRODUCTIVITY MEASURE AND IMPLICIT SHADOW SHARES

***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:

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

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 et al. (1994) showed that the Malmquist 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.

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

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

***Technology and distance functions***

We assume, as in Färe et al. (1998), that for each time period t = 1,…., T the production technology describes the possibilities for the transformation of inputs $x^t$ into outputs $y^t$. 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):

$$L^t = \{(y^t,x^t): \text{such that } x^t \text{ can produce } y^t\} \quad (3)$$

This technology 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 $y^t$:

$$D_0^t(x^t, y^t) = \min \{\theta : (\theta x^t, y^t) \in L^t\} \quad (4)$$

where $\theta$ 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[2]. This distance function in (4) can be calculated for the output and input vectors of production unit (PU) 'o' $(y_o,x_o)$ using DEA-like linear programming:

[2] 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).

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

s.t. (5)

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

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

$$\lambda \geq 0$$

where ***i*** represents the ***r*** different PUs that define the PPS, ***k*** are ***m*** outputs and ***j*** are ***n*** inputs . The efficiency score obtained ($\theta_o$) will take values between 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 (5) 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):

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

s.t. (6)

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

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

As explained in Coelli and Prasada Rao (2001), to solve this problem we normalize the ratio by imposing: $\sum_{j=1}^{n} w_j x_{ij} = 1$ , modifying problem (6) as follows (with p and w different from $\rho$ and $\omega$):

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

$$s.t.$$

$$\sum_{j=1}^{n} \omega_j x_{ij} = 1 \tag{7}$$

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

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

For this problem, 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 (4) has the equivalent dual formulation:

$$D_0^t(x^t, y^t) = \max\left\{ \frac{\rho y^t}{\omega x^t} : \frac{\rho y^t}{\omega x^t} \leq 1 \forall (y^t, x^t) \in L^t \right\} \tag{8}$$

They interpret this distance function as “the return to the dollar (Georgescu-Roegen, 1951) 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 $\rho_k$ and $\omega_j$ are respectively output k and input j shadow prices with respect to technology $L^t$.[3]

### *Implicit Input Shares in DEA Analysis*

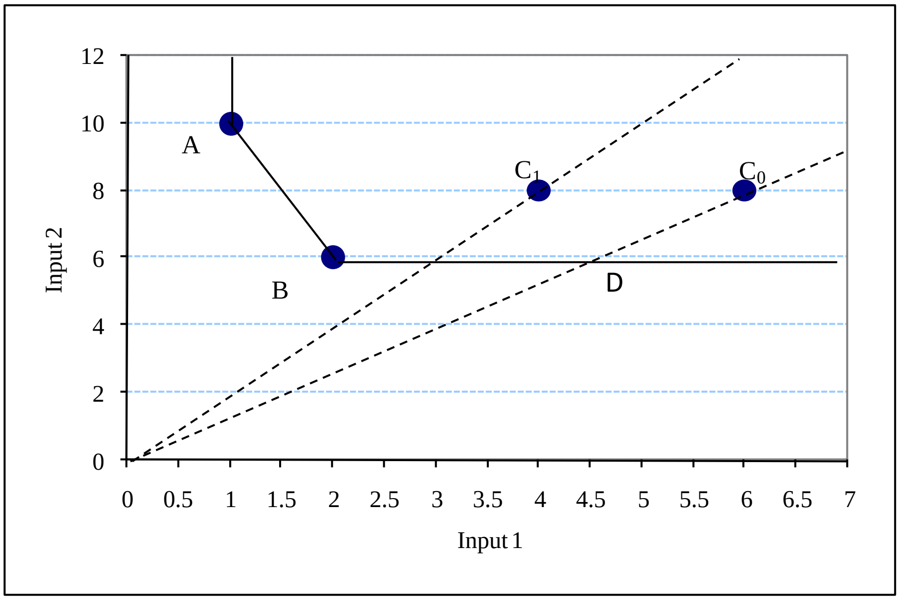
Even though a priori price information is not needed, the DEA procedure still uses prices to estimate efficiency and non-parametric Malmquist indices. The LP used in DEA estimates defines a set of weights for the inputs and outputs that minimize the distance of each assessed PU to the technological frontier (maximize its efficiency). These weights can be interpreted as implicit shadow prices, and if the choices of input-output bundles made by each PU 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.

Because of the lack of information about prices, in most of the literature on efficiency and non-parametric TFP analysis, allowing total flexibility in choosing shadow prices has been considered to be one of the major advantages of DEA methods to measure efficiency and productivity (Pedraja-Chaparro, 1997). However, total flexibility for the estimation of shadow prices has been criticized on several grounds, given that these

[3] There exists a vector of shadow prices for any arbitrary input-output vector, however, these prices not need to be unique.

estimates can prove to be inconsistent with prior knowledge or accepted views on relative prices or cost shares (e.g. zero shadow prices).

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




Source: Adapted by authors from Coelli and Prasada Rao (2001)

Figure 1 shows how zero shadow prices occur and how they can affect TFP measures.[4] The figure represents three PUs 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 (5) this means that the constraint for *input 1* is not binding for DMU $C_0$:

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

[4] We follow here the discussion in Coelli and Prasada Rao (2001)

A non binding constraint for *input 1* in problem (5) means that this input will have a zero shadow price in the dual problem (7). With zero shadow price input substitution is not defined. 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.

## 3. INTRODUCING CONSTRAINTS TO SHADOW SHARES TO ESTIMATE MALMQUIST INDICES

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] (7). We define as in section 2 the standard distance function where $\rho$ and $\omega$ 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),

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[5] 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.

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

s.t. (11)

$$\sum_{i=1}^{m} \omega_i^t x_{io}^t = 1$$

$$\sum_{r=1}^{s} \rho_r^t y_{rj}^t - \sum_{i=1}^{m} \omega_i x_{ij}^t \leq 0$$

$$a_{io}^t \leq \omega_i^t x_{io}^t \leq b_{io}^t \quad \mathrm{i} = 1,..., \mathrm{m}$$

$$\rho, \omega \geq 0$$

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.

We introduce information on the likely value of the shares of the different inputs from Evenson and Dias Avila (2007) to define the bounds for the input shares. 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, and that estimates by Evenson and Dias Avila are based in FAO data as the one used here, we utilize 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.

**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 |

Source: Authors using information from Evenson and Dias Avila, 2007.

Table 1 shows bounds of input shares derived from estimates by Evenson and Dias Avila (2007) for developing countries. The pattern of upper and lower bounds shows that Latin America separates from other regions for its low shadow price for land and high incidence of labor, tractors and fertilizers in production costs. In contrast with Latin America, South Asia has the lowest contribution to costs of labor and tractors and one of the highest of animal stock. The incidence of fertilizers in South Asia is lower than in Latin America, similar to that in SE Asia and much higher than in Africa. Shadow shares in SE Asia are similar to those in South Asia but with potentially higher incidence of labor and lower incidence of animal stock. In the case of SSA, while land and animal stock shares are similar to those in South Asia, labor shares are closer to those in Latin America, tractor shares are the lowest among all regions and fertilizer shares are only above those in MENA.

***Comparing constrained and unconstrained shadow shares***

Using the shadow share bounds from Evenson and Dias Avila we calculate constrained shares derived from efficiency estimates using shadow share bounds as in LP problem (11), and compare these estimates to shares from unconstrained estimations of efficiency from LP problem (7). Data used are from 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 outputs used in agriculture. We use one output (agricultural production measured in international dollars) and five inputs (labor, land, fertilizer, tractors and animal stock) for 106 countries. We estimate efficiency for all these countries, including 29 countries in Sub-Saharan Africa (SSA), 21 in Latin America, 13 in Asia and 11 in the Middle Easter and North Africa (MENA).

Simple average constrained and unconstrained shares for different regions are presented in Table 2. Results show that the unconstrained DEA measurements of efficiency underestimates the share of land and labor and overestimates shares of other inputs, according to values in Evenson and Dias Avila (2007). However, the importance of these differences varies significantly across regions. Shadow shares for Latin America are close to those within the bounds defined using Evenson and Dias Avila’s estimates. Unconstrained shares tend to overestimate the importance of land and tractors and underestimate labor by magnitudes in the order of 20 to 30 percent (-37 percent in the case of labor in Central America). Asia’s unconstrained shares tend to overestimate expected shares of tractors and animal stock and underestimate labor shares. The major differences occur with estimates in SSA and MENA. In the case of SSA, the unconstrained results show very low shares for labor and land, while highly overestimate shares for animal stock, tractors and fertilizer. For MENA countries, unconstrained results overestimate animal stock and fertilizer shares and underestimate land, labor and tractor shares.

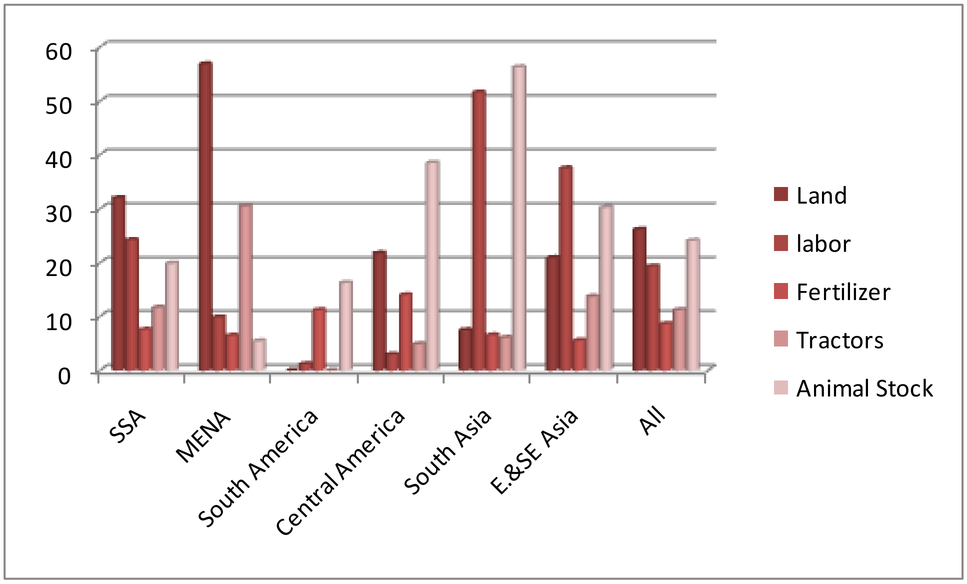
**Table 2. Average input shares from unconstrained and constrained estimations of efficiency**

| | 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 |
| Difference (%)[c] | | | | | | |
| All | -11 | -33 | 31 | 73 | 25 | |
| Sub-Saharan Africa | -54 | -73 | 189 | 94 | 200 | |
| Central America | 20 | -37 | 16 | 30 | 25 | |
| South America | 19 | -27 | 22 | 0 | 0 | |
| South Asia | 0 | -63 | 42 | 83 | -8 | |
| East & Southeast Asia | -8 | -53 | 25 | 217 | 36 | |
| Middle East & N.Africa | -66 | -54 | -33 | 370 | 150 | |

Notes: a) Includes Mexico. b) Lower bound for labor was relaxed, allowing lower values than measures in Evenson and Dias Avila (2007). c) Calculated as: ((UCS-CS)/CS)*100, where UCS is unconstrained share and CS is constrained share.
Source: Author's estimation

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 imposed to estimate shares. Figure 2 shows the incidence of zero input prices.

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




Source: Author's estimation

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 for land). The percentage of countries with zero fertilizer and tractor shadow prices is much lower (9-11 percent respectively).

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 including the use of land in almost 60 percent of all MENA countries, in one third of SSA countries and in one fourth of countries in other regions. Also, labor is given a zero share in estimates of productivity in half of the Asian countries while in the case of animal stock, half of South Asian countries, 40 percent of Central American countries, and 30 percent of other Asian countries show zero shadow prices.

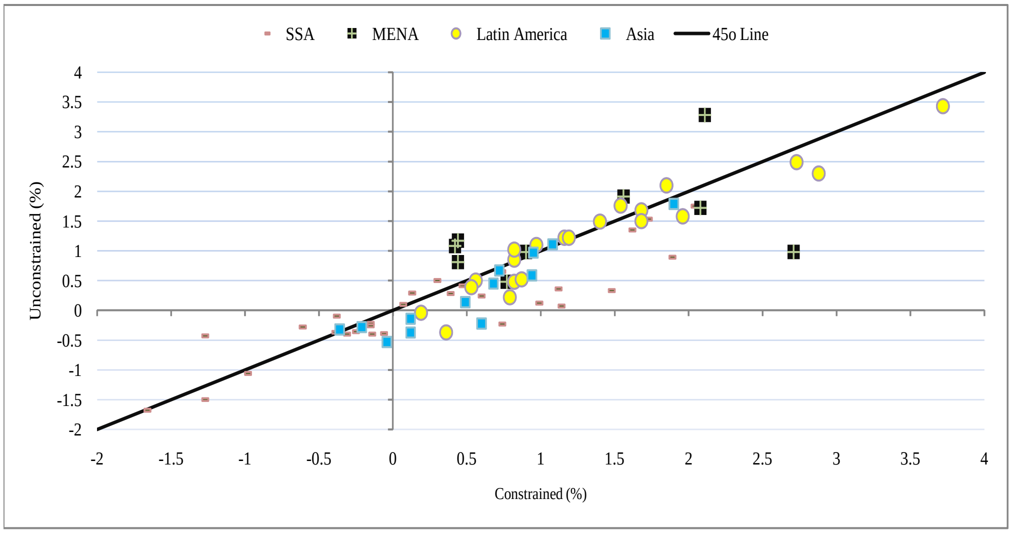
***Malmquist index with constrained and unconstrained shadow input shares***

The incidence of zero shadow prices in our distance measures could affect estimates of distances and TFP changes. In this section we take a closer look at unconstrained and constrained estimates of TFP to determine how these estimates differ and to derive implications for the use of unconstrained Malmquist indices.

We look first at individual countries' estimates. Figure 3 shows values of average annual growth rates from the Malmquist index, where each point in the figure represents a country and the coordinates of each point are the TFP growth rates estimated using constrained and unconstrained shadow shares. Points on or close to the $45^{o}$ line are those for which the estimation method used does not affect, or has little effect on TFP estimates. Simple visual inspection of the figure shows that Latin American countries show small differences between estimates (most points on or close to the 45o line), while estimates for Asia and SSA appear to be more affected by the estimation method. In order to determine more formally if there is a difference between the constrained and the unconstrained TFP and distance estimates we approximate the sampling distributions of DEA estimators by Monte Carlo simulations. To do this, we define a variable X equal to the difference between the average annual growth of the constrained TFP estimate and the average annual growth of the unconstrained estimate. In this way we determine 67 values of X, one for each country in our sample. We sample repeatedly 30 values from the set of 67 values and calculate the mean for each sample obtaining in this way a distribution of the average of each sample of 30 values and test the null hypothesis that the mean of this distribution is equal to zero, implying that there is no difference between constrained and unconstrained TFP and distance estimates. Results of the Monte Carlo simulations are presented in table 3

On average for the group of 67 countries, the difference between unconstrained and constrained TFP growth rates is 0.10 points in absolute terms with a standard error of 0.078 and a p value of 0.202. This means that the null hypothesis of no difference between TFP estimates cannot be rejected. However, there are differences between estimates of the TFP components and of distance functions. On average, constrained and unconstrained estimates of distances and of changes in efficiency result in significantly different values.

**Figure 3. Average TFP growth 1964-2003 estimated using constrained and unconstrained shadow prices and differences between measures for different countries[(a)]**




Source: Authors' estimation

Note: a) Each point represents a country, differences between estimates are revealed by the distance between each point and the 45$^{o}$ line.

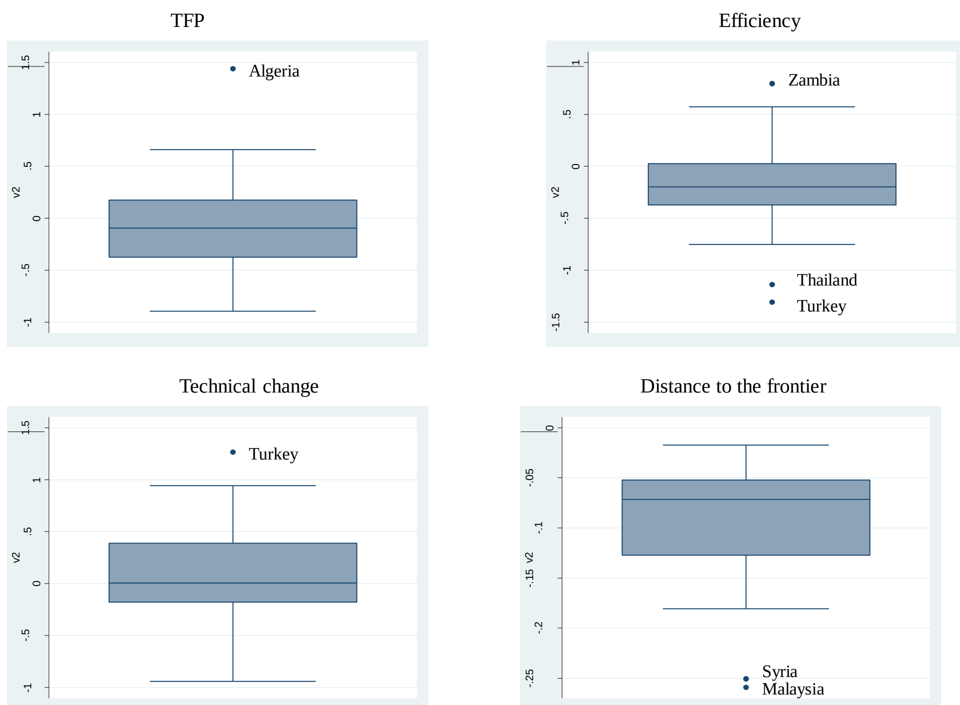
Having shown that there are significant differences between average estimated distances and efficiency changes using constrained and unconstrained shadow prices, we look now at estimates at the country level. To verify the presence of outliers, we generate a boxplot of the differences between the two TFP estimates and its components (Figure 4). As expected there are 10 outliers, all of them in MENA and Africa. For these countries, controlling unrestricted values of input shadow shares result in significantly different TFP measures than the ones obtained with restricted shares.

**Table 3: Bootstrapped mean and standard error of the distribution of variable X defined as the difference between constrained and unconstrained estimates of distance functions and TFP estimates**

| | Mean | Standard Error | Z | P>\|Z\| |
|---|---|---|---|---|
| TFP | -0.100 | 0.078 | -1.28 | 0.202 |
| Technical change | 0.077 | 0.083 | 0.93 | 0.353 |
| Efficiency change | -0.175 | 0.068 | -2.59 | 0.010 |
| Distance to the frontier | -8.676 | 0.949 | -9.14 | 0.000 |

Source: Authors' estimation
Note: 20,000 replications of samples of size 30 from the set of 67 countries

**Figure 4. Boxplot of differences between measures estimated using constrained and unconstrained input shadow shares**




Source: Authors' estimation

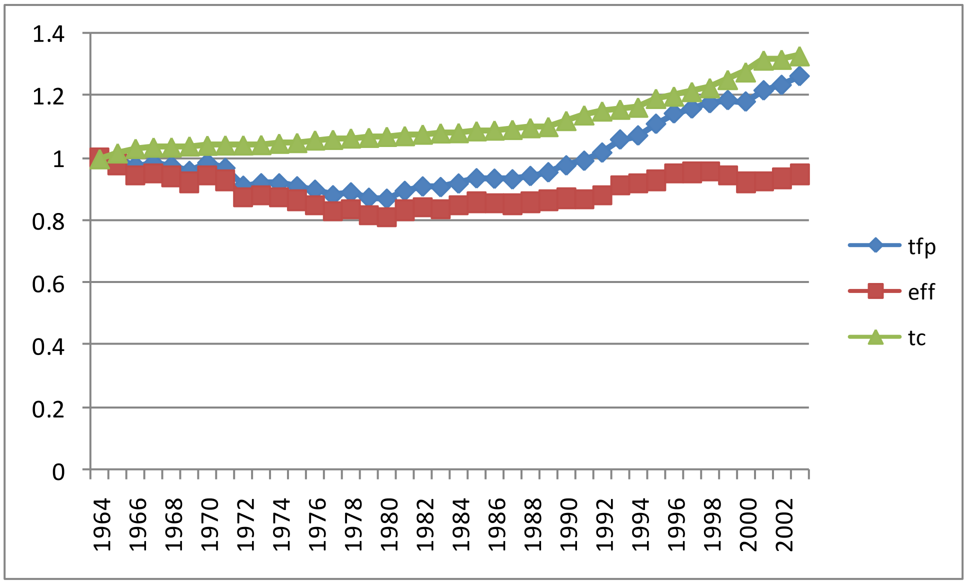
We conclude that the incidence of zero and "unusual" shadow prices could has a significant effect on estimates of the Malmquist index. Even though we use a large sample of more than a hundred countries to define the PPS used as the reference for the distance estimates, we still find a high incidence of zero shadow prices. This incidence is higher among African countries which appear to differ from other countries in the sample in terms of their combination of inputs. 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 when reporting TFP measures of individual countries.

## 4. TFP GROWTH AND AGRICULTURAL PERFORMANCE IN DEVELOPING COUNTRIES, 1961-2006

In this section we use the constrained TFP estimates to measure productivity growth in developing countries. A weighted average of the 67 countries considered in this study indicates that agricultural productivity grew for this group of countries at an annual rate of 0.58 percent between 1964 and 2003. This poor performance however, hides great variability across regions, countries and time. We can distinguish two main periods with contrasting performance. During 1964-1983, agricultural TFP growth was negative (-0.48) but recovers in 1984-2003 with an average growth rate of 1.65 percent during this period. 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).[6]

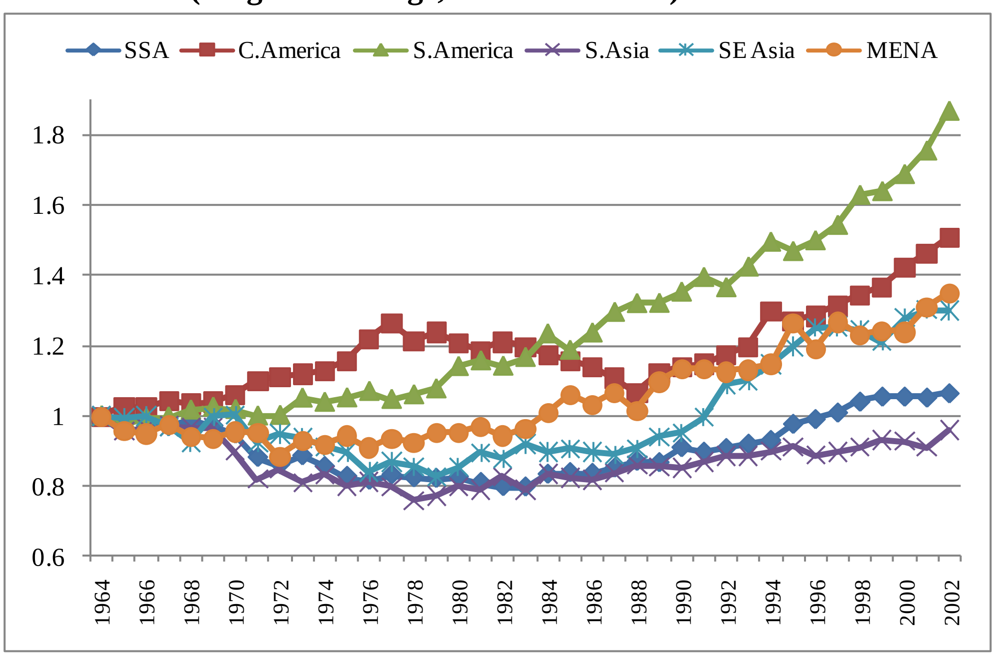
[6] Results at the country level can be found in the Appendix.

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




Source: Elaborated by authors

**Figure 6 Cumulative agricultural TFP growth in different developing regions 1964-2003 (weighted average, index in 1964=1)**




Source: Elaborated by authors

At the regional level, Latin America shows the best performance, with sustained TFP growth in South America since the late 1970s and strong growth in Mexico and Central America since the late 1980s. 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.

## 5. CONCLUSIONS

In this paper we analyze input shadow prices determined by the linear programming problems used to estimate the DEA Malmquist productivity index. 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. We then impose bounds in the estimation of shares to ensure that the most important outputs and inputs are included in the TFP estimation, while keeping those values within the rank expected *a priori*. With this information we estimate non-parametric Malmquist indices using unconstrained and constrained estimates of distance functions for 72 developing countries. We found that the incidence of zero and "unusual" shadow prices could have a significant effect on TFP measures of some of the countries in our sample. This incidence is higher among African countries which appear to differ from other countries in the sample in terms of their combination of inputs. These results confirm the importance of reporting shadow prices in DEA estimates of Malmquist indices and eventually the need to constrain shadow input shares when interested in TFP measures of individual countries.

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.

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## APPENDIX

### Table A.1 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 A.1 (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 |

**Table A.2 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 A.2 (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 |

**Table A.3 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 A.3 (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 |