A Bayesian Total Factor Productivity Analysis of Tropical Agricultural Systems in Central-Western Africa And South-East Asia

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Abstract

This paper computes and analyses total factor productivity (TFP) growth rates for tropical agricultural systems in Central-Western Africa and South-East Asia. Two regions that despite sharing common agro-ecological conditions, have pursued different adoption rates of green revolution technology and have reported dissimilar yields per hectare. A panel data set is constructed for the period 1987-2007 from the FAOSTAT database. A Bayesian stochastic frontier model with country specific temporal variation in technical efficiency is estimated. Technical efficiency estimates reveal that there is substantial room for improvement in both continental sub-sets and that TFP estimates show on average larger rates of growth for South-East Asian countries as compared to Central-Western African countries. Results indicate that TFP is mostly driven by technical change and countries such as Benin, and Gambia display catch-up.

Keywords: Bayesian Inference, Stochastic Production Frontier, Time Varying Technical Inefficiency, Total Factor Productivity Growth, Tropical Agricultural Systems

JEL Classification: C15, D24, O47

Introduction

According to the World Bank Development Report of 2008, in the last two decades, South Asian countries have on average experienced a 50% increase in cereal yield (roughly from 1.6 to 2.4 tons per hectare) and a 30% reduction in poverty (from 45% to 30% poverty incidence), while in Sub-Saharan Africa both yields and poverty were unchanged (at approximately 1 ton per hectare and always close to a 50% poverty incidence) (Ravallion and Chen, 2004). In a world scenario of increasing competition for resources where demand for food is expected to increase by 70% in 2050 (due to the effect of population growth and per capita incomes) (FAO, 2004), greater growth in agricultural supply must be based on enhanced productivity growth..

However, recent academic findings suggest that the positive effects of the green revolution technology in maize, wheat and rice yields have started to stagnate or decline. For instance, Adlas and Alchot (2006) analyzed long-term yield growth of rice in various ecosystems and states of India between 1967 and 1999. Their findings indicate that yield growth (of areas where adoption of modern varieties and irrigation coverage were nearly complete) slowed down during the late green revolution period (i.e. after 1985). Pingali (2007) argues that the decline in the productivity growth rates of the three primary cereals may be attributed to: 1) Degradation of the land resource base due to intensive cultivation 2) Declining infrastructure and research investment and 3) Increasing opportunity cost of labor (mainly arising from the off-farm sector).

In the meantime, recent developments in genetically modified crops are promoted by large multinationals within the private sector[1]. Pingali (2007) has termed these new

[1] According to Byerlee and Fischer (2001) private sector investment in agriculture research has exceed the combined investment of all public sector research institutes worldwide. At the beginning of the 2000´s, the top ten multi-nationals

advances in modified crops as the "gene revolution" and stresses that developing countries will face high transaction costs in order to access and use these new technologies which unlike with the green revolution, its research outputs are in private hands. Clearly, this puts high pressure on the poor farmers' ability to produce at the level of the best production frontier possible and to adequately face global market competition. Lastly, Pingali and Traxler (2002) also highlight gaps in private research coverage which may be unfavorable for developing economies´ farmers. Firstly because private sector interest in tropical agricultural systems with small market potential will continue to be limited (as crop studies are selected according to potential market size). Secondly, attention is mainly given to relatively few crops (maize, soybean, cotton and vegetable), as a result, crops in marginal or stress prone environments would be excluded.

Thus, this paper measures and compares total factor productivity (TFP) growth in agriculture for 20 countries belonging to the humid[2] and sub-humid[3] agro-ecologies of tropical Africa and Asia (i.e. mix of rainforest and woodland savannas) between 1987 and 2007. The sample comprises countries under a common agro-ecological setting which is advantageous for the following reasons. First, the effects outside the control of farmers such as weather (usually captured in the random error term) can be partially mitigated. Second, these countries share similar soils and water constraints. Third, unlike other agro-ecological zones (i.e. highland, arid or semi-arid) there is higher pressure on manual labor as cultivation involves clearing of woody vegetation and/or burning along with frequent fertilization practices and plague control. Fourth, in these zones there is a relatively low level of livestock (particularly in the humid areas of central-western Africa due to trypanosomiasis and other diseases), a situation which also contributes to the shortage of soil nutrients. Overall, as Bloom and Sachs (1998: 3) argue, tropical agriculture (particularly food production) is faced with chronic problems of low yields and fragility due to low photosynthetic potential, high evapotranspiration, variable rainfall, highly weathered soils, veterinary diseases and plant and animal pests. In other words, by focusing on countries which are dominated by these shared agro-climatic conditions it will be possible to better evaluate their agricultural production performance. Since TFP captures how efficiently inputs are utilized in the production process, it becomes an adequate performance measure for it allows explaining differences in productivity across countries based on differences in technology and efficiency (Comin, 2007: 260).

The present paper addresses the following key questions: What countries are making the most and the least efficient use of their available inputs? What has driven TFP growth rates in the past two decades and what has been its general trend? Hence, a parametric stochastic frontier analysis is considered rather useful because it allows identifying the effects of changes in technical efficiency, technology and (economies of) scale for a set of countries which share similar agro-climatic constraints. Results will reveal if countries are converging towards the frontier thus experiencing a positive efficiency change (or vice versa) or if the frontier itself is shifting over time indicating advances in technology as

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in the sector invested US$ 3 000 million of which 50% was devoted to biotechnological projects. On the other hand, the Consultative Group of International Agricultural Research (CGIAR-the largest international public sector supplier of agricultural technologies) spent US$ 300 million of which less than 10% was devoted to biotechnology.

[2] Humid zone: Annual rainfall > 1200 mm; Growing season > 270 days. Three different production systems can be identified: (1) Shifting cultivation or slash and burn system; (2) Permanent home gardens where natural forest is replaced and household waste is used as nutrients; 3) Lowland rice production (Powell and William, 1993).

[3] Sub-humid zone: Annual rainfall = 600 – 1200 mm; Growing season = 120 – 270 days.

well as if countries have improved the scale of operations towards the technologically optimum scale (i.e. scale change). Since the adoption of modern seed varieties has been faster and more widely in Asia than in other developing regions (with the exception of wheat in Latin America), it will also be possible to observe if there are any noticeable differences in terms of green revolution technology use and effect[4].

The posed research questions in the framework of tropical agricultural systems are highly relevant not only in terms of food supply and food security but also in terms of an effective access to inputs, efficient use of natural resources and poverty reduction. Econometric results will therefore serve to better understand the TFP trends and the particular challenges of stagnated agricultural areas characterized by unfavorable environmental contexts (such as that of the tropics) and/or where green revolution technology effects have declined (or where these have not been successfully adopted[5]).

The article is divided into five sections. In section 2 the theoretical model used to measure factor productivity growth is presented. While in section 3, the Bayesian stochastic frontier estimation used is described. Section 4 outlines the characteristics of the dataset. Section 5 presents and discusses the results of the empirical model. Section 6 concludes.

Theoretical Model

This section describes the model used to measure factor productivity growth. Consider a production frontier model where the agricultural production of country *i* (i=1,..,N) at time *t* (t=1,..,T), Y_{it}, is produced using the input array, $\mathbf{X}_{it}$ constituted by land $\left(X_{1it}\right)$, machinery $\left(X_{2it}\right)$, labor $\left(X_{3it}\right)$, fertilizer $\left(X_{4it}\right)$ and livestock $\left(X_{5it}\right)$ respectively. Assuming a common best-practice technology, f, brings to a production frontier that leads to the maximum amount of output that can be produced from a given level of inputs as given by:

$$Y_{it} = f\left(\mathbf{X}_{it}\right)\tau_i \xi_{it}, \tag{1}$$

where τ_i measures the deviation of actual from maximum feasible output, so-called technical inefficiency (i.e. $0 < \tau_{it} \leq 1$ where $\tau_{it} = 1$ means full technical efficiency) and ξ_{it} is the random error part of the frontier (e.g. measurement error, specification error, effect of weather and disease).

A transcendental logarithmic (i.e. translog) production frontier is selected for its flexibility in measuring TFP growth. The translog functional form allows for variation of production elasticities at each data point and for non-neutral Hicksian technical change. The empirical model is specified as follows:

$$y_{it} = \beta_0 + \sum_{n=1}^{N} \beta_n x_{itn} + \beta_t t + \frac{1}{2}\sum_{n=1}^{N}\sum_{m=1}^{N} \beta_{nm} x_{itn} x_{itm} + \frac{1}{2}\beta_{tt} t^2 + \sum_{n=1}^{N} \beta_{nt} x_{itn} t - z_i + \varepsilon_{it} \tag{2}$$

[4] According to Pingali (2007) by the 1970´s more than 50% of the wheat and 40% of the rice grown in Asia consisted of modern varieties. By the 1990´s more than 80% of wheat and 60% of rice, maize and other cereals in Asia were modern varieties. In contrast, wheat is the only crop in sub-Saharan African for which modern variety adoption exceeds 40%.

[5] Byerlee and Moya (1993) confirmed that improved seed-fertilizer technologies for wheat were less widely adopted in marginal environments worldwide and had less of an impact there than in favored environments. Likewise, it was found that almost full adoption of wheat and rice high yielding varieties (HYV) had been achieved in irrigated environments by the mid-1980´s, but very low adoption in environments with scarce rainfall, or poor water control (in the case of rice). In addition, while HYV´s of wheat provided yield gains of 40% in irrigated areas, with modest use of fertilizer, in dry areas gains were often no more than 10% - another importance for comparing similar agro-climatic zones.

where lower case letter (y,x) indicate natural logs of upper case letters (Y,X), $\beta=(\beta_0,\beta_1,\ldots,\beta_k)$ the unknown parameters to be estimated, t a time trend in order to account for technological change, the inefficiency $z_i=-ln(\tau_i)$ is assigned a non-negative random variable, $\varepsilon_{it}=ln(\xi_{it})$ a symmetric distribution with mean zero. Note that β_0-z_i plays the role of an individual effect as usually encountered in a panel data framework.

In this paper a generalization of Battese and Coelli's (1992) function proposed by Cuesta (2000) is used. The Cuesta's (2000) function is specified as

$$z_{it}=z_i\times exp[\eta_i(t-T)] \tag{3}$$

where the temporal pattern of inefficiency effects (i.e. η_i) is now a country-specific parameters responsive to different patterns of temporal variations among countries. The technical efficiency of each country in each year can be obtained through the conditional expectation of $exp(-z_{it})$, given the value of $\varepsilon_{it}-z_i$.

In order to measure the Malmquist Index (MI) (Caves et al. 1982:1394) of TFP growth the efficiency, technical change and scale components need to be calculated. The efficiency change component is given by:

$$EC_{is}=exp(z_{it}-z_{is})=z_{is}/z_{it} \tag{4}$$

The technical change component requires to evaluate the partial derivatives of the production frontier with respect to time using the data for the *i*-th country in period s and t. Then the technical change between the adjacent periods s and t can be derived through the geometric mean of the aforementioned partial derivatives. In the case of a translog specification, this is equivalent to the exponential of the arithmetic mean of the log derivatives as given by:

$$TC_{is}=exp\left\{\frac{1}{2}\left[\frac{\partial y_{is}}{\partial s}+\frac{\partial y_{it}}{\partial t}\right]\right\} \tag{5}$$

To detect potential scale change effects, scale change is introduced in computing TFP following Orea (2002), who uses Diewert's quadratic identity to derive a MI. The scale change component is given by:

$$SC_{is}=exp\left\{\frac{1}{2}\sum_{n=1}^{N}[\zeta_{isn}SF_{is}+\varepsilon_{itn}SF_{itn}](x_{isn}/x_{itn})\right\} \tag{6}$$

where $SF_{is}=(\varepsilon_{is}-1)/\varepsilon_{is}$, $\zeta_{is}=\sum_{n=1}^{N}\zeta_{isn}$ and $\zeta_{isn}=\frac{\partial y_{is}}{\partial x_{isn}}$. Each single component is then summed up to recover the MI of TFP growth.

The Bayesian Stochastic Frontier Model

This section describes the Bayesian stochastic frontier estimation used. Van den Broeck et al. (1994) introduced Bayesian stochastic frontier models. Stochastic frontier models require numerical integration methods for their complexity, as such the Markov Chain Monte Carlo (MCMC) introduced by Koop et al. (1995) is the most appropriate method. In this paper, a MCMC Gibbs sampler following Griffin and Steel (2007) is used. The form of the likelihood function assumes that the inefficiency components z and ε are independent and that z is a vector of unknown parameters. For simplicity equation (2) is rewritten after stacking all variables into matrices so that we can avoid the t subscript as follows:

$$y_i = \beta_0 + \sum_{n=1}^{N} \beta_n x_{in} + \beta_t t + \frac{1}{2}\sum_{n=1}^{N}\sum_{m=1}^{N} \beta_{nm} x_{in} x_{im} + \frac{1}{2}\beta_{tt} t^2 + \sum_{n=1}^{N} \beta_{nt} x_{in} t - z_i \iota_T + \varepsilon_i \tag{7}$$

where ι_T is a T-vector of ones.

The standard corresponding likelihood function is

$$p\left(y \middle| \beta, \sigma_v^{-2}, z\right) = \prod_{i=1}^{N} \frac{\left(\sigma_v^{-2}\right)^{\frac{T}{2}}}{\left(2\pi\right)^{\frac{T}{2}}} \left\{ \exp\left[-\frac{1}{2}\sigma_v^{-2}\left(\varepsilon_i\right)'\left(\varepsilon_i\right)\right]\right\} \tag{8}$$

where

$$\varepsilon_i = y_i - \beta_0 + \sum_{n=1}^{N} \beta_n x_{in} + \beta_t t + \frac{1}{2}\sum_{n=1}^{N}\sum_{m=1}^{N} \beta_{nm} x_{in} x_{im} + \frac{1}{2}\beta_{tt} t^2 + \sum_{n=1}^{N} \beta_{nt} x_{in} t - z_i \iota_T .$$

The dependent variable is assumed to follow a normal distribution

$$y_{it} \sim N\left(\beta_0 + \sum_{n=1}^{N} \beta_n x_{tin} + \beta_t t + \frac{1}{2}\sum_{n=1}^{N}\sum_{m=1}^{N} \beta_{nm} x_{itn} x_{itm} + \frac{1}{2}\beta_{tt} t^2 + \sum_{n=1}^{N} \beta_{nt} x_{itn} t - z_i, \sigma^2 \right) \tag{9}$$

where $N\left(\mu, \sigma^2\right)$ is a normal distribution with mean μ and variance σ^2. The inefficiencies, z_i, capturing the difference between best practice and actual output, are assumed to have a truncated normal distribution as given by

$$z_i \sim N^{+}\left(\varsigma, \lambda^{-1}\right) \tag{10}$$

where λ has a gamma distribution

$$\lambda \sim Ga\left(\phi, \lambda_0\right) \tag{11}$$

with $\lambda_0 = \phi\left(\log\left(r^*\right)\right)^2$. Appropriate prior values for ϕ and r^* are documented in the literature[6] (see for example Tsionas 2000; Griffin and Steel 2004). The temporal pattern of inefficiency effects (see equation (6)), η_i, follows a zero mean normal distribution whit variance Γ

$$\eta_i \sim N\left(\underline{\eta}, \underline{\Gamma}\right). \tag{12}$$

Regularities conditions are imposed to ensure that input elasticities are nonnegative (i.e. monotonicity in input elasticities) at sample mean. Monotonicity is imposed through the value of the first order coefficients by imposing a truncated normal distribution as given by

$$\beta_i \sim N^{+}\left(\underline{\beta_i}, \underline{\Sigma}\right), \text{where } i = 1,\ldots,5 \tag{13}$$

and a multivariate normal distribution for the second order remaining coefficients

$$\beta_i \sim N\left(\underline{\beta_i}, \underline{\Sigma}\right), \text{where } i = 6,\ldots,27 \tag{14}$$

and gamma distribution for the white noise precision, $\left(\sigma_v^{-2}\right)$, as given by

$$\sigma_v^{-2} \sim Ga\left(\underline{a_0}, \underline{a_1}\right). \tag{15}$$

Several priors on the precision and the specification of the parameters are specified following Griffin and Steel (2007). The parameter for Γ is set to 0.25 reflecting prior indifference between increasing and decreasing efficiency, the parameters for the white

[6] In this paper ϕ and r^* are set to 5 and 0.8 respectively. The last assumes to reflect a prior median efficiency of 0.8.

noise precision gamma distribution are set to 10^{-3}, and the variance of the multivariate normal distribution for the parameters β are set to 10^{-7}. The relevant conditional distribution of the stochastic frontier model are omitted to save space but are available upon request.

Data Description

The data was obtained from the FAOSTAT database[7] (FAO, 2010). As mentioned, the sample includes 20 countries, twelve from Central-Western Africa: Benin, Cameroon, Congo, Democratic Republic of Congo, Gabon, Gambia, Ghana, Guinea, Ivory Coast, Nigeria, Senegal and Togo[8] and eight from South-East Asia: Cambodia, Indonesia, Lao´s People Democratic Republic, Malaysia, Myanmar, Philippines, Thailand and Vietnam. Since the data was collected for a 21 year period (1987 to 2007), the panel consists of 420 observations. The net agricultural production valued at 1999-2001 international dollar prices is used as output variable. Information was also collected for five key agricultural inputs: land, labor, machinery, fertilizers and livestock. Land comprises arable land, permanent crops land and the area for permanent meadows and pastures. It is measured in 1000 hectares (Ha)[9]. Machinery is measured in terms of number (in 1000´s) of agricultural tractors in use (excluding garden tractors and there is no reference to horsepower tractors). Agricultural labor is estimated in terms of economically active population in agriculture including their non-working dependents (also measured in 1000´s of individuals). The fertilizers variable consists of an aggregation of Nitrogen (N), Potassium (P2O2) and Phosphate (K20) consumed in agriculture and expressed in (1000´s) tones of nutrients. Lastly, livestock is constructed by aggregating five categories of animals (buffaloes, cattle, pigs, sheep and goats) into sheep equivalent values by using the same conversion factors as those used by Coelli et al (2005). Table 1 presents descriptive statistics for the complete dataset.

Table 1 Descriptive Statistics 1987-2007.

Variables (Unit)	Avg	Min	Max	Std
Agr Output (1000 Int $)	5670768.84	59531.00	36777490.00	7057844.68
Land (1000 Ha)	14546.07	611.00	78500.00	20832.45
Machinery (1000 # tractors)	30.17	0.03	830.00	15662.99
Labor (1000 person)	8555.66	192.00	47783.00	18113.04
Fertilizers (1000 tones)	387.87	0.00	3699.06	16059.21
Livestock (1000 Sheep Equiv)	43275.00	535.57	221432.54	49238.89

Source: FAO (2010).

[7] This common source allows for comparing data across countries as they are calculated on same standards.
[8] Equatorial Guinea, Guinea Bissau, Liberia and Sierra Leone were excluded from the sample selection due to large segments of missing data in the series of fertilizers and livestock.
[9] Arable land: land under temporary agricultural crops (multiple-cropped areas are counted only once), temporary meadows and for mowing or pasture, land under market and kitchen gardens and land temporarily fallow (less than five years). The abandoned land resulting from shifting cultivation is not included in this category. Permanent crops: land cultivated with long term crops which do not have to be replanted for several years, land under trees and shrubs producing flowers and nurseries. Permanent meadows and pastures land used permanently (five years or more) to grow herbaceous forage crops, either cultivated or growing wild (wild prairie or grazing land) (FAO, 2010).

Results and Discussion

This subsection discusses the estimates obtained. For simplicity and ease of interpretation all variables, before estimation, are rescaled in order to have unit means. The estimated parameters[10] of the stochastic production frontier are presented in Table 2[11]. The input elasticities are at sample average 0.6778, 0.0074, 0.3829, 0.0350, and 0.4658 for land, machinery, labor, fertilizer and livestock respectively.

Table 2 Bayesian estimated parameters of the stochastic production frontier 1987-2007.

Parameter	Avg	Std	MC error	2.5%	Median	97.5%
β0	1.3680	0.2307	0.0092	1.0430	1.3220	1.9470
β1	0.6778	0.0823	0.0018	0.5179	0.6771	0.8389
β2	0.0074	0.0070	0.0000	0.0002	0.0053	0.0260
β3	0.3829	0.0844	0.0023	0.2188	0.3822	0.5492
β4	0.0350	0.0088	0.0002	0.0179	0.0350	0.0523
β5	0.0447	0.0316	0.0006	0.0020	0.0394	0.1180
βt	0.0290	0.0055	0.0002	0.0189	0.0289	0.0401
β11	-0.0452	0.1252	0.0033	-0.2866	-0.0456	0.1983
β12	0.0003	0.0207	0.0002	-0.0412	0.0006	0.0400
β13	-0.1650	0.0823	0.0017	-0.3260	-0.1655	-0.0019
β14	-0.0392	0.0094	0.0001	-0.0577	-0.0392	-0.0209
β15	0.3733	0.0796	0.0019	0.2201	0.3721	0.5319
β1t	0.0042	0.0020	0.0000	0.0005	0.0042	0.0082
β22	-0.0123	0.0100	0.0001	-0.0318	-0.0122	0.0073
β23	0.0471	0.0261	0.0005	-0.0046	0.0473	0.0976
β24	0.0158	0.0056	0.0001	0.0048	0.0158	0.0267
β25	-0.0753	0.0235	0.0003	-0.1218	-0.0754	-0.0293
β2t	0.0000	0.0006	0.0000	-0.0012	0.0000	0.0012
β33	-0.3824	0.1043	0.0011	-0.5877	-0.3822	-0.1775
β34	0.0127	0.0080	0.0000	-0.0026	0.0126	0.0289
β35	0.2597	0.0788	0.0016	0.0940	0.2636	0.4045
β3t	-0.0053	0.0017	0.0000	-0.0085	-0.0053	-0.0019
β44	0.0010	0.0033	0.0000	-0.0054	0.0009	0.0076
β45	-0.0061	0.0069	0.0000	-0.0198	-0.0060	0.0071
β4t	0.0002	0.0007	0.0000	-0.0010	0.0002	0.0015
β55	-0.2944	0.0589	0.0009	-0.4047	-0.2964	-0.1726
β5t	0.0052	0.0015	0.0000	0.0023	0.0052	0.0083
βtt	0.0000	0.0002	0.0000	-0.0004	0.0000	0.0005
λ	2.5590	0.9755	0.0168	1.0700	2.4170	4.8360
σ^{-2}	782.4000	148.5000	1.0690	533.8000	768.0000	1114.0000

Note: Subscripts on coefficients indicate inputs: 1 = land; 2 = machinery; 3 = labor; 4 = fertilizer; 5 = livestock; t = trend.
Source: Own estimates.

[10] The Gibbs sampler was run for one chain with burn-in of 5,000 iterations, with 195,001 retained draws and a thinning to every 50th draw in order to decrease the autocorrelation of the chain. The accuracy of the estimation was checked by comparing the Monte Carlo (MC) error with the corresponding posterior standard deviation. When the MC errors are relatively low as compared to the standard deviation, convergence can be assumed (Ntzoufras 2009:120).

[11] Density plots for all parameter estimates are omitted to save space but are available upon request.

On one hand, the relatively larger input elasticities for land as compared to the elasticity for livestock is likely to be attributed to the low level of livestock production particularly in the humid areas of Central-Western Africa as mentioned in the introductory section. On the other hand the considerable contribution of labor to agricultural production (labor input elasticity of 0.38) underlines the likely manual labor intensive cultivation practices of the tropical agricultural systems. All the first-order coefficients have an unambiguous positive association with the response variable, implying that the production frontier is increasing in inputs. The sum of these input elasticities is 1.15, indicating that the technology locally exhibits very mild increasing return to scale at sample mean. The annual percentage change in output due to technical change is estimated to be 2.9 percent. In order to depict non-monotonic technical change a time-squared variable is introduced in the model, plus time interacted with each input variable to allow for non-neutral technical change. The coefficient of time squared indicates that the rate of technical change is increasing at a constant rate through time. The coefficient of time interacted with the land, machinery, labor, fertilizer and livestock input variables are positive for land, fertilizer and livestock and negative for labor and very close to zero but positive for machinery. This suggests that technical change has been land-, machinery-, fertilizer- and livestock-saving but labor-using over the time considered. The parameters capturing the temporal variation of the technical inefficiency are presented in Table 3.

Table 3 Bayesian estimated parameters of the temporal variation of inefficiency (η)

Country	Avg	Std	MC error	2.5%	Median	97.5%
Benin	0.0074	0.0041	0.0001	-0.0005	0.0074	0.0149
Cameroon	-0.0037	0.9983	0.0022	-1.9590	-0.0057	1.9560
Congo	-0.0029	0.9980	0.0024	-1.9560	-0.0019	1.9520
DR Congo	0.0006	0.9982	0.0023	-1.9580	0.0024	1.9630
Gabon	-0.0021	1.0010	0.0024	-1.9610	-0.0033	1.9520
Gambia	0.0042	0.9995	0.0023	-1.9470	0.0037	1.9670
Ghana	0.0016	0.9978	0.0023	-1.9590	0.0015	1.9620
Guinea	-0.0045	1.0000	0.0024	-1.9630	-0.0044	1.9530
Iv Coast	-0.0009	1.0010	0.0023	-1.9670	-0.0007	1.9520
Nigeria	0.0026	0.9974	0.0022	-1.9580	0.0013	1.9700
Senegal	0.0026	0.9982	0.0022	-1.9600	0.0029	1.9510
Togo	-0.0009	1.0010	0.0023	-1.9590	-0.0034	1.9620
Cambodia	0.0011	0.9993	0.0021	-1.9600	0.0044	1.9640
Indonesia	0.0021	1.0020	0.0023	-1.9630	0.0038	1.9700
Laos	-0.0010	1.0000	0.0022	-1.9650	-0.0023	1.9540
Malaysia	0.0040	1.0030	0.0023	-1.9650	0.0078	1.9620
Myanmar	-0.0041	1.0010	0.0023	-1.9730	-0.0027	1.9600
Philippines	0.0011	0.9999	0.0022	-1.9630	0.0035	1.9530
Thailand	0.0002	1.0010	0.0023	-1.9550	-0.0031	1.9630
Vietnam	-0.0006	1.0020	0.0023	-1.9700	-0.0001	1.9620

Source: Own estimates.

The estimated parameters of the temporal variation by country show that for nine countries technical efficiency is declining over time whereas for the remaining eleven countries it is increasing. Positive trends in the temporal variation of technical inefficiency are predominant in the South East Asian countries. The smallest and largest temporal variations of technical inefficiency are found for Guinea and Benin respectively; indicating that over time the latter is moving further away and the former closer to the frontier. This information is relevant to understand whether countries are catching-up/converging to the best practice frontier.

Average technical efficiency scores by country are in Table 4. Technical efficiency scores range from 0.093 for Guinea to a maximum of 0.822 for Malaysia with an unweighted average over all countries of 0.332. The average technical efficiency scores imply that the countries were on average producing about 33.2 percent of the outputs that could be produced using the observed input quantities. The unweighted average technical efficiency scores were 0.217, and 0.505 for the African and Asian countries respectively.

Table 4 Average technical efficiency scores by country 1987-2007.

Country	Avg	Std	MC error	2.5%	Median	97.5%
Benin	0.5184	0.1328	0.0048	0.2557	0.5211	0.7792
Cameroon	0.2359	0.0626	0.0023	0.1150	0.2364	0.3575
Congo	0.1036	0.0397	0.0012	0.0412	0.0986	0.1964
DR Congo	0.2530	0.0690	0.0024	0.1233	0.2521	0.3937
Gabon	0.1894	0.0851	0.0025	0.0669	0.1748	0.3960
Gambia	0.1750	0.0885	0.0029	0.0570	0.1564	0.3991
Ghana	0.2632	0.0656	0.0025	0.1327	0.2650	0.3882
Guinea	0.0926	0.0254	0.0010	0.0449	0.0922	0.1436
Iv Coast	0.2981	0.0822	0.0030	0.1435	0.2968	0.4646
Nigeria	0.1661	0.0963	0.0033	0.0408	0.1454	0.3991
Senegal	0.1110	0.0308	0.0012	0.0537	0.1102	0.1737
Togo	0.1949	0.0537	0.0019	0.0941	0.1941	0.3055
Cambodia	0.2427	0.0606	0.0023	0.1225	0.2441	0.3577
Indonesia	0.3981	0.1268	0.0040	0.1769	0.3883	0.6761
Laos	0.4784	0.1344	0.0048	0.2298	0.4747	0.7549
Malaysia	0.8219	0.1521	0.0055	0.4415	0.8643	0.9950
Myanmar	0.4605	0.1172	0.0042	0.2256	0.4645	0.6750
Philippines	0.5361	0.1256	0.0046	0.2723	0.5449	0.7559
Thailand	0.4314	0.1155	0.0041	0.2067	0.4326	0.6549
Vietnam	0.6666	0.1817	0.0060	0.3076	0.6679	0.9766

Source: Own estimates.

These results imply that for a given set of inputs, the African countries in the sample obtain suboptimal output level as compared to Asian countries: in other words for a given output level they are using a suboptimal input level. However, the relatively low level of technical efficiency for both Central-Western African and South-East Asian countries, suggest that these countries have the potential to make large improvements in productivity through a more efficient use of inputs. Considering the temporal variation of technical inefficiency in Table 3 and the level of technical efficiency in Table 4, it appears that Guinea, Congo and Gabon are making the worst use of inputs among the countries considered and at the same time their suboptimal input use is worsening over time moving further away from the best practice frontier. While Gambia endowed with an initially low level of technical inefficiency is positively moving closer to the frontier over time.

Table 5 presents the decomposition of TFP growth for each country for the 1987-2007 period into efficiency, technical and scale change. TFP growth ranges from 4.83 for

Nigeria to 2.07 for Gabon, with an unweighted overall average of 2.95. While the estimated unweighted average annual TFP growth is 2.9 and 3.1 percent for the African countries and South East Asian countries respectively, the weighted TFP growth rates for the total (Central-Western Africa plus South-East Asia) net value of agricultural production shows that the productivity contribution of South-East Asia is almost two times the one of Central-Western Africa. This is partly based on the fact that despite having all countries portraying productivity growth, highest variability in terms of TFP change is found within the Central-Western African sub-set.

Table 5 Decomposition of TFP growth by country. Average annual changes in % 1987-2007.

Country	Efficiency Change	Technical Change	Scale Change	TFP Change
Benin	0.7009	2.5674	0.2499	3.5182
Cameroon	-0.3490	3.2897	0.1376	3.0784
Congo	-0.2742	2.3582	-0.0090	2.0750
DR Congo	0.0538	2.3579	0.0125	2.4242
Gabon	-0.2009	2.3108	-0.0394	2.0705
Gambia	0.4007	1.8596	0.0093	2.2696
Ghana	0.1479	2.7180	0.2213	3.0873
Guinea	-0.4299	2.9611	0.4838	3.0150
Iv Coast	-0.0810	3.0045	0.1552	3.0787
Nigeria	0.2457	4.1476	0.4337	4.8271
Senegal	0.2505	3.1012	0.2254	3.5771
Togo	-0.0822	2.2019	0.0724	2.1921
Cambodia	0.1059	2.6827	0.4788	3.2674
Indonesia	0.2014	3.2246	0.0962	3.5222
Laos	-0.0912	2.4421	0.4941	2.8451
Malaysia	0.3826	2.8102	-0.0236	3.1692
Myanmar	-0.3901	2.9269	0.3806	2.9174
Philippines	0.1052	2.8642	0.0326	3.0021
Thailand	0.0199	3.0240	-0.0002	3.0437
Vietnam	-0.0593	2.5135	-0.2801	2.1742

Source: Own estimates.

Efficiency change ranges from -0.43 for Guinea to 0.70 for Benin, with an unweighted average of 0.04 with nine countries (three Asian and six African) showing negative efficiency changes. Technical change ranges from 1.86 for Gambia to 4.15 for Nigeria, with an unweighted average of 2.77 with none of the countries showing productivity regress. The estimates suggest that productivity growth was mostly driven by technical change, thus signaling the importance of access to improved technology in the sector. Scale change ranges from -0.28 for Vietnam to 0.49 for Laos, with an unweighted average of 0.16 with Thailand displaying very little negative scale changes.

Conclusions

In this paper, we have analyzed the differences in agricultural production performance of selected countries of tropical Africa and Asia by focusing on TFP growth between 1987 and 2007. Our results show that for a given best practice technology South-East Asian countries are making a more efficient use of their agricultural inputs when compared to Central-Western African countries. Although South-East Asian countries during the green revolution adopted High Yielding Varieties (HYV's) at a faster rate than Central-Western African countries, efficiency scores for both sub-sets imply that a suboptimal use of agricultural inputs is present. Malaysia and Benin are the most technical efficient countries, whereas Cambodia and Guinea fare the least technical efficient countries for South-East Asia and Central-Western Africa respectively.

Regarding TFP in both regions, positive growth rates are observed over the period considered with Indonesia and Nigeria being the best performing countries, whereas Laos and Gabon being the least performing countries. TFP appears to be mostly driven by upward movements of technology over time. The latter coincides with Pingali and Heisey (2001) who emphasize that the necessary future increases in food productivity growth will depend on positive shifts of the crop yield frontier. For a number of countries, particularly in Central-Western Africa, efficiency change is declining with a negative impact on productivity. This is something that deserves particular attention in countries like Gabon, Congo and Guinea already characterized by very low level of technical efficiency. Most of the countries display mild positive scale changes whereas Malaysia, Congo and Gabon show negative scale change being Vietnam almost at its optimal scale. Two countries display catch up with the best practice technology (i.e. Malaysia): Benin and Gambia.

The results of this study suggest that the tropical agricultural systems of Central-Western Africa and South-East Asia must reassess their input usage practices mainly to reduce inefficiency by implementing and adopting best management practices in order to achieve the highest yields possible. This also reinforces the importance of timely and sufficient access to technological developments; an issue which is crucial for the improvement of tropical agricultural systems in the coming years. Moreover, given that most of the projected population growth (i.e. nine billion by 2050) is expected to occur in poor countries and that world food demand is expected to double within the next three and four decades (Ruttan, 2002), food security will remain a sensible issue, particularly in areas (such as that of the humid and sub-humid tropics) where increases in scientific and technical efforts to improve productivity are not adequately pursued or sustained.

Care should be taken when interpreting results since these are always conditional on the data and a number of assumptions used for estimation (e.g. functional form, error generating process, etc.). While we may not believe the literal interpretation of the magnitude of some results, we believe that our results have drawn attention to the relative performance challenges of the agricultural sector in Central-Western Africa and South-East Asia. Finally, further research is needed to understand the major institutional, political and socio-economic constraints at work in the countries considered.

References

Adlas J and Achoth L (2006) Is the green revolution vanishing? Empirical evidence from TFP analysis for rice. International Association of Agricultural Economics Conference. Australia. August 2006.

Battese GE and Coelli T (1992) Frontier production functions, technical efficiency and panel data: with application to paddy farmers in India. Journal of Productivity Analysis 3(1-2):153-169.

Bloom D and Sachs D (1998) Geography, demography, and economic growth in Africa. Brookings panel on economic activity. Washington DC. September 1998.

Byerlee D and Fischer K (2001) Accessing modern science. Biodevelopments–International institute Inc, Cornell, Ithaca, NY (IP Strategy Today, No. 1-2001).

Byerlee D and Moya P (1993) Impacts of international wheat breeding research in the developing world, 1966-1990. Mexico, D.F.: International Maize and Wheat Improvement Center (CIMMYT).
Caves DW, Christensen LR and Diewert WE (1982) The economic theory of index numbers and the measurement of input, output and productivity. Econometrica 50(6): 1393-1414.
Coelli TJ and Prasada Rao DS (2005) Total factor productivity growth in agriculture: a Malmquist index analysis of 93 countries. 1980-2000. Agricultural Economics 32(1): 115-134.
Comin D (2007) Total factor productivity. In: Aghion P and Howitt PW (eds)
Endogenous Growth Theory. MIT Press: Cambridge.
Cuesta R (2000) A production model with firm specific temporal variation in technical efficiency: with application to Spanish dairy farms. Journal of Productivity Analysis 13(2): 139-158.
FAO (2004) The state of food and agriculture 2003-04. Agricultural biotechnology: meeting the needs of the poor? Rome: Food and Agriculture Organization.
FAO (2010). FAOSTAT. URL: http://faostat.fao.org/site/291/default.aspx Last accessed 15/12/2010
Griffin JE and Steel M (2007) Bayesian stochastic frontier analysis using WinBUGS. Journal of Productivity Analysis 27(3):163-176.
Griffin JE and Steel M (2004) Flexible mixture modeling of stochastic frontier. University of Warwick, Technical Report, Warwick.
Koop G, Steel MFJ and Osiewalski J (1995) Posterior analysis of stochastic frontier models using Gibbs sampling. Computational Statistics 10: 353-373.
Ntzoufras I (2009) Bayesian Modeling Using WinBUGS. Wiley: Hoboken
Orea L (2002) Parametric decomposition of a generalized Malmquist index. Journal of Productivity Analysis 18(1):5-22.
Pingali P (2007) Will the Gene Revolution reach the poor? – Lessons from the Green Revolution. 7th Manshold Lecture. Wageningen, January 26, 2007.
Pingali P and Heisey P (2001) Cereal-crop productivity in developing countries: past trends and future prospects. In: Alston JM, Pardey PG and Taylor M (eds.) Agricultural Science Policy. IFPRI and Johns Hopkins University Press: Washington DC.
Pingali P and Traxler G (2002) Changing locus of agricultural research: will the poor benefit from biotechnology and privatization trends. Food Policy 27: 223-238.
Powell JM and William TD (1993) An overview of mixed farming systems in sub-Saharan Africa. In: Powell JM, Fernandez-Rivera S Williams TO and Renard C (eds.) Livestock and Sustainable Nutrient Cycling in Mixed Farming Systems of Sub-Saharan Africa:1-36
Ravallion M and Chen S (2004) How have the World's Poorest Fared since the early 1980's? World Bank Research Observer 19 (2): 141-70.
Ruttan V (2002) Productivity Growth in World Agriculture: Sources and Constraints. The Journal of Economic Perspectives. 16 (4):161-184.
Tsionas EG (2000) Full likelihood inference in Normal-gamma stochastic frontier models. Journal of Productivity Analysis 13(3):183-205.
van den Broeck J, Koop G, Osiewalski J and Steel MFJ (1994) Stochastic frontier models: a Bayesian perspective. Journal of Econometrics 61(2): 273-303.
World Bank (2008) Development Report 2008. Washington DC.