Knowledge center of

NOVAFRICA

NOVA SCHOOL OF BUSINESS & ECONOMICS

Working Paper Series

Thirty Years of Economic Growth in Africa

João Amador
Banco de Portugal e Nova School of Business and Economics

António R. dos Santos
Banco de Portugal e Nova School of Business and Economics

ISSN 2183-0843

Working Paper No 1802

August 2018

NOVAFRICA.ORG

NOVAFRICA Working Paper

NOVAFRICA | Nova School of Business and Economics - Faculdade de Economia da Universidade Nova de Lisboa
Campus de Carcavelos | 2775-405 Carcavelos – Portugal | T: (+351) 213 801 673 | F: (+351) 213 801 105 | www.novafrica.org

Thirty Years of Economic Growth in Africa*

João Amador
Banco de Portugal
Nova SBE

António R. dos Santos
Banco de Portugal
Nova SBE

August 2018

Abstract

This paper examines the contribution of employment, capital accumulation and total factor productivity (TFP) to economic growth in African countries over the period 1986-2014. The methodology consists in the estimation of a translog dynamic stochastic production frontier for a set of 49 African economies, thus allowing for the breakdown of TFP along efficiency developments and technological progress. Although the heterogeneity amongst African countries poses a challenge to the estimation of a common production frontier, this is the best approach to perform cross-country comparisons. The results of our growth accounting exercise are more accurate for the contribution of input accumulation and TFP to GDP growth than for the separation between contributions of technological progress and efficiency. We conclude that economic growth patterns differ across African countries but they have been almost totally associated to input accumulation, notably in what concerns capital. The experience of Egypt, Nigeria and South Africa - the three largest African economies - confirms this pattern.

Keywords: Africa, Development, Growth Accounting, Dynamic Stochastic Frontiers
JEL Codes: C11, O47, O55

*Address: Banco de Portugal, Economics and Research Department, R. Francisco Ribeiro 2, 1150-165 Lisboa - Portugal. E-mails: jamador@bportugal.pt; ammsantos@bportugal.pt. The opinions expressed in the paper are those of the authors and do not necessarily coincide with those of Banco de Portugal or the Eurosystem. The authors thank Sónia Cabral and Pedro Freitas for useful comments and suggestions. Errors and omissions are the sole responsibility of the authors.

1 Introduction

Africa has recorded a very good economic performance since the turn of the century. The average annual GDP growth rate in African countries reached 5.0 per cent in the period 1999-2014, which contrasts with a rate of 2.9 per cent in the period 1985-2000. In addition, there was a meaningful progress in a number of social indicators (Zedillo et al. (2015)).

These positive developments have gained attention from the recent economic development literature (e.g., Rodrik (2014), Harchaoui and Ungor (2018) and King and Ramlogan-Dobson (2015)). In particular, a relevant question in the literature is whether the so-called "African growth miracle" is putting an end to a secular malaise of weak economic development or if it is just the result of temporary factors. Some authors point out a strong increase in commodity prices and the subsequent attraction of foreign investment as the main driver for the strong economic growth in the initial years of the century (McMillan and Harttgen (2014)). It is referred that the commodity boom that benefited many African economies is closely linked with Chinese demand, spurred by its own strong growth. Other authors argue that there is more than a commodity boom to explain recent African growth (Annunziata et al. (2014)). This strand of literature has been pointing towards structural improvements in terms of agricultural productivity, political and economic governance and higher households' purchasing power, as well as demographic trends such as a growing labour force, urbanization, better education, health care and longer life expectancy. These latter dimensions are typically interpreted as both drivers and consequences of GDP growth, thus starting a virtuous cycle of economic development. Moreover, the improvement of macroeconomic conditions, notably in terms of reductions in external debt, as well as current account and fiscal deficits, has also been contributing to the good recent overall economic performance.

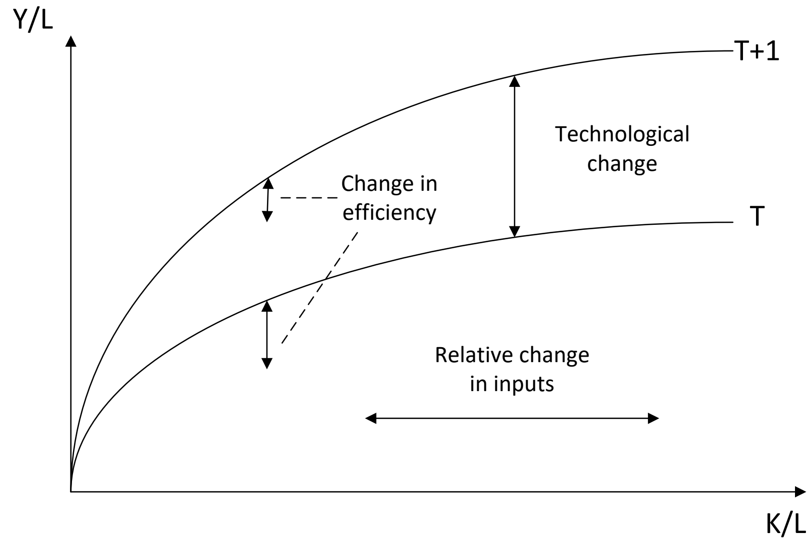
It is important to frame the analysis about the recent African economic developments within the classic conceptual framework of growth theory. Seminal contributions to economic growth theory comprise Solow (1956) and later the works of Romer (1986, 1990) and Lucas (1988). These basic models motivated progress in the empirical literature, which divided into two different paths. One strand of the literature bases on cross-country regressions to associate countries' characteristics to growth performance. Initial contributions in this area are those of Baumol (1986), Barro (1991) and Sala-Martin (1997). The other strand of empirical literature, generically labeled as "growth accounting", bases on the seminal work of Solow (1957), which decomposes economic growth in the economy into inputs' accumulation and total factor productivity (TFP) developments.

The growth accounting literature is very large and it is quite relevant for the analysis of economic growth. Although growth accounting exercises are silent about causality, they remain a very useful diagnostic tool and they are as important as studies focusing on specific drivers of development, which mostly base on case-studies. The classic growth accounting exercises compute the contributions of input accumulation and TFP developments to observed GDP growth in each country. However, performing separate growth accounting exercises for individual countries raises issues of comparability. The relevant growth benchmark is how peer countries perform and not what each individual country achieves. Therefore, unless these exercises bring together information from several countries to estimate a common stochastic production frontier, it is impossible to disentangle TFP developments along the impact of technological progress that is potentially available for all countries and changes in individual efficiency. This is a key feature for the interpretation of economic developments but it is typically disregarded in empirical growth accounting exercises.

This paper contributes to the literature by estimating Africa's dynamic stochastic production frontier in two periods, making it possible to perform a growth accounting exercise that is meaningful and comparable across countries. More specifically, we use Bayesian methods in order to obtain the parameters of a translog dynamic stochastic production frontier for the overall set of African economies and compute the contribution of different factors to economic growth - employment, capital accumulation and TFP, which is separated into technological growth (shifts in the frontier) and efficiency developments (change in distance to the frontier). The efficiency developments signal the ability to improve the utilization of existing inputs, no matter the origin of the existing distortions, while the contribution from technological progress assesses whether the existing mix of inputs in the country is in line with the most productive techniques and highly valued outputs. Figure 1 illustrates these contributions in a simplified two-dimensional dynamic production frontier.

In the last decades, the progress on computation capabilities led to the increased utilization of Bayesian inference techniques in many areas of economic research. These methods have been used to estimate stochastic production frontiers both at aggregate and micro levels (see Griffin and Steel (2004)). Bayesian inference methods are quite flexible and have proven to be particularly suitable when samples are small, in contrast with their maximum likelihood counterparts. The initial applications of Bayesian methods to growth accounting are those of Koop et al. (1999, 2000), upon which we rely in this paper.

Figure 1: Stylized dynamic stochastic production frontier



The paper focuses on the three decade period of 1985-2014, which is split into two periods of 16 years (15 yearly growth rates). The first period corresponds to the years 1985-2000 and is characterized by Africa's low economic growth in comparison with other regions of the world. The second period corresponds to the years 1999-2014 and outlines a period of growth acceleration that is due not only to favorable terms of trade and greater foreign aid, but also to better policies (Arbache et al. (2008)). The two periods considered correspond to different phases of super-cycles of commodities (Erten and Ocampo (2013)). Their prices presented a downward trend in the first period that reversed after the turn of the century. Therefore, the two periods selected contrast recent positive African economic performance with years when growth developments were disappointing, even if partly due to shifts in commodity prices.

The paper concludes that capital accumulation was the major driver of recent economic growth in Africa. The contribution of labour input was mildly positive and stable in the two periods, reflecting the fact that the demographic dividend in African growth is still to be materialized. The contributions of technological progress to GDP growth are small when compared with those of capital and labour and most countries benefited from positive contributions in only one of the two periods. Moreover, most countries recorded positive contributions from efficiency in the period 1985-2000 but only about half of them maintained this situation in the period 1999-2014, meaning that structural reform may have lost momentum in some economies.

The paper is organized as follows. In the next section we briefly compare the distribution

Table 1: GDP growth in Africa and in the world

	1985-2000					1999-2014				
	Simple average	Median	Min	Max	Stdev	Simple average	Median	Min	Max	Stdev
Africa	2.9	2.8	-4.2	13.6	2.8	5.0	4.4	-1.5	14.4	2.5
America	3.1	2.9	0.0	6.7	1.5	3.2	3.5	0.6	6.3	1.5
Asia	4.9	4.6	0.6	8.5	2.0	5.1	4.8	-0.7	11.3	2.5
Europe	2.6	2.5	-1.4	6.2	1.8	2.0	1.8	0.1	4.6	1.2
Oceania	2.8	2.9	2.3	3.4	0.6	2.4	2.5	1.8	2.9	0.6

Source: Authors' calculations based on Penn World Tables v8.

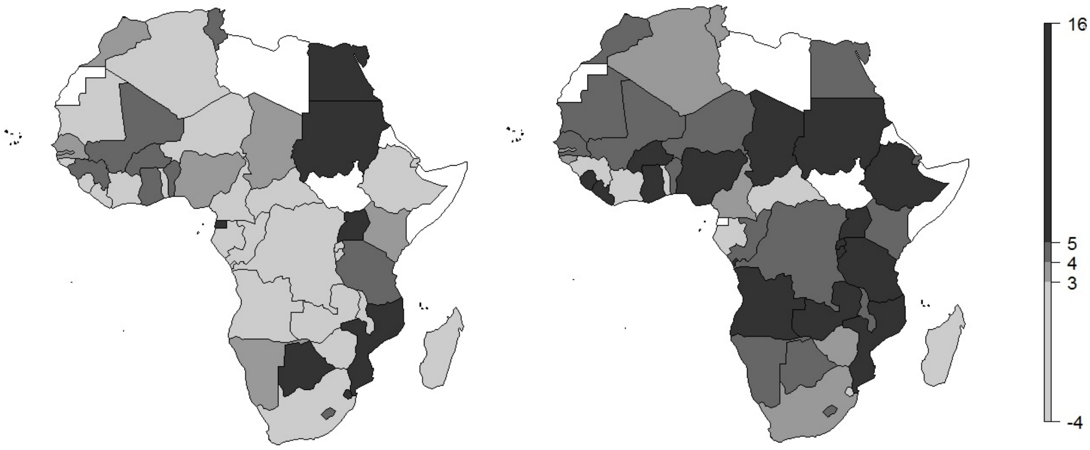
of GDP growth in African countries with those of other continents in the two periods considered. Section 3 describes the methodology for the estimation of the dynamic stochastic frontier and the database. Section 4 presents the results, comparing the contribution of inputs, efficiency and technological progress for total GDP growth in each period. Moreover, the section discusses the elasticities of inputs, analyses changes in the position and shape of the frontier in the two periods considered and highlights the results obtained for the three largest African economies - South Africa, Nigeria and Egypt. Finally, section 5 offers some concluding remarks.

2 African growth in perspective

It is a well established fact that different initial development levels, as well as idiosyncratic country and regional shocks, lead to high dispersion in the distribution of GDP growth rates across countries. Table 1 presents some descriptive statistics on GDP growth rates per continent in the average of the periods 1985-2000 and 1999-2014, thus placing the African situation in a broader perspective.

In the period 1985-2000, African countries recorded an average growth rate of 2.9 per cent. This is less than what was recorded in the American continent and, especially, in Asia. Only Europe and Oceania have shown an average GDP growth rate slightly below that of Africa in this period. Given the lower average development level in Africa, this can be classified as a disappointing performance. Table 1 also shows that cross-country GDP growth dispersion in Africa was much larger than in other continents, with a standard deviation of 2.8 percentage points (p.p.) and the difference between the best and worst performing countries larger than

Figure 2: GDP growth rates (percentage)



(a) 1985-2000 (b) 1999-2014

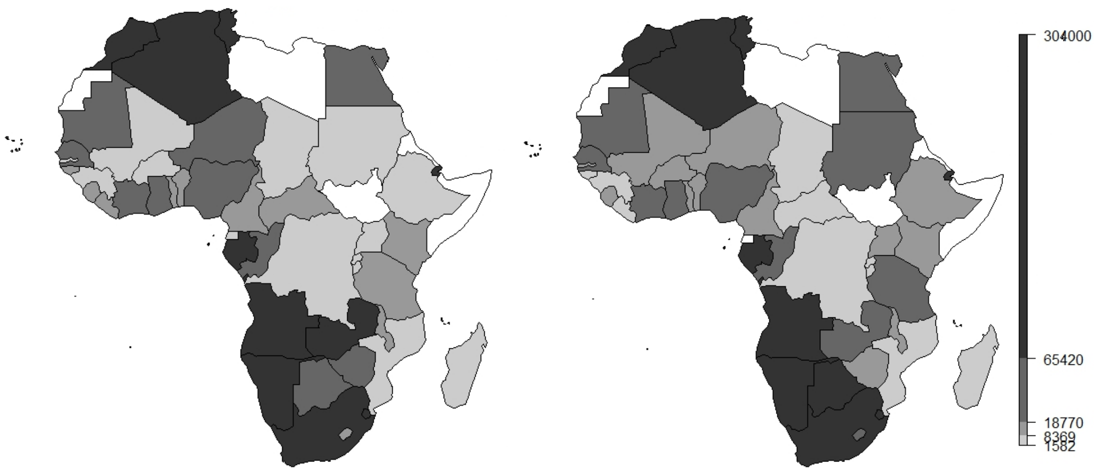
Notes: Authors' calculations based on Penn World Tables v8. The scale is defined by the quartiles of the distribution of growth rates observed in the periods 1985-2000 and 1999-2014.

17 p.p. The scenario has changed in the period 1999-2014. The average GDP growth in Africa accelerated to 5.0 per cent, which is close to the figure recorded for Asia and well above that of the remaining continents. However, the standard deviation of growth rates inside Africa remained large in the most recent period (2.5 p.p.).

The two panels of Figure 2 map the average GDP growth in African countries in 1985-2000 and 1999-2014 using a scale of four colours, defined by the quartiles of the cross-country distribution of growth rates observed in the two periods. Therefore, taking the two maps together, the scale and the number of countries in each interval are the same. The darker colours in panel b) show that economic performance clearly improved in the period 1999-2014 relatively to 1985-2000 for most African countries. The highest GDP growth rates were recorded in sub-Saharan countries and in those immediately North of Austral Africa. Conversely, Central and Northern African countries grew relatively less.

Capital-labour ratios are key ingredients in any growth accounting exercise because the ability to increase capital per worker is a basic feature in classic growth models. Figure 3 presents the capital-labour ratios in 1985 and 2014 using a scale of four colours, defined by the quartiles of the cross-country distribution of this variable in the two periods. The comparison of the two panels in Figure 3 shows that capital-labour ratios increased from 1985 to 2014 in many countries. Nevertheless, one striking feature of the data is the strong positive skewness of the distribution of these ratios. In 2014, Equatorial Guinea and Gabon show very high

Figure 3: Capital per worker (2011 Dollars per worker)



(a) 1985

(b) 2014

Notes: Authors' calculations based on Penn World Tables v8. The scale is defined by the quartiles of the distribution of ratios observed in the periods 1985-2000 and 1999-2014.

ratios, while central Africa countries like Burundi, the Democratic Republic of Congo and Guinea post much lower levels of capital per worker. These huge disparities, reflected in the scale of Figure 3, relate to the productive structure of the economies, notably the existence of natural resources.

3 The stochastic frontier approach

The underlying assumption in the current exercise is the existence of an African production frontier, which can be statistically identified because there are countries laying in its different segments. Conceptually, it means that since all countries have equal access to the same technology if two of them have equal labour and capital endowments the one with higher GDP is more efficient, i.e., it stands closer to the African stochastic production frontier.

The validity of the assumption on the existence of an international production frontier is worthwhile discussing, notably in the African context. Although it is accepted that knowledge about production techniques and about the relative value of goods and services is widely accessible across countries in the world, its dissemination may take a long time to materialize, for example due to institutional or geographical barriers. For instance, heavy licensing procedures or other regulatory costs may deter the entry of firms with new technologies. In addition, specific technological innovation in agriculture may be effective only in a given climate region, while countries in other locations may be unable to implement it, even with similar capital and labour endowments. In this vein, Basu and Weil (1998) discuss the speed of international dissemination of technological progress and its implications in terms of growth, arguing that it occurs at a slower pace than the diffusion of knowledge. Therefore, the time that elapses until a country effectively adopts the technological innovations in the production systems reflects in its relative productive efficiency.

The dissemination of knowledge is faster amongst economies with less distortions and lower institutional barriers. In addition, it is easier within a group of countries that is homogeneous in terms of institutional setup and with geographical proximity, which supports the decision to estimate the African stochastic production frontier. Nevertheless, it can be argued that technologies available in countries located in other continents are relevant to identify the African production possibilities. For example, some Asian, Latin American or European countries face some structural conditions close to those prevailing in Africa, thus providing useful information for the identification of production possibilities. However, the selection of some non-African countries for the estimation of the production frontier would be discretionary. Alternatively, the utilization of all available countries in the database, although offering the largest possible mix of inputs to identify the international production frontier, could excessively deviate from the African reality. Therefore, our option was to estimate the frontier for the full set of African countries and test the robustness of results using the entire Penn World Tables dataset, which broadly covers the world. Reassuringly, the most important growth accounting results obtained for Africa remain unchanged.

Another issue is the assumption on the pace of technological progress in the set of countries used in the estimation. The assumption made is that technology evolves in a linear way along each of the two periods defined in the paper. This implicitly means that there is an average speed for the adoption of new technologies across countries and specific lags or leads are captured by the efficiency component. In a similar context, Koop et al. (1999) extensively tested alternative formulations for the dynamics of the production function, namely a time specific model, where frontiers are totally independent in time, a quadratic trend model and a linear trend model under constant returns to scale. The authors concluded that the linear trend model is the best performer in terms of in-sample fit, ability to distinguish the components of TFP and number of parameters to compute.

Our paper considers two 16-year periods (15 annual rates) and results for the growth accounting exercises are presented in terms of average contributions to GDP growth. It should be noted that the length of the periods considered is sufficient to average out short run fluctuations in the macroeconomic variables.

Regarding the functional form of the production function, a translog specification is used. This formulation encompasses, as a special case, the logarithmic transformation of the Cobb-Douglas production function and it is more flexible than the latter. In fact, a major limitation of the logarithmic transformation of the Cobb-Douglas production function is the absence of interaction terms between labour and capital. Temple (2006) argues that the assumption of a Cobb-Douglas specification may lead to spurious results in economical and statistical terms. The problem is magnified because traditional growth accounting exercises treat TFP as unobservable (omitted variable). Conversely, if the researcher identifies a good proxy for TFP and the data are actually generated by a translog, a suitable specification accurately recovers the original parameters and rejects the Cobb-Douglas.

Classical econometrics allow for the estimation of stochastic production functions through maximum likelihood methods.[1] However, the Bayesian methods are suitable when samples are small because they allow for inferences without relying on asymptotic approximations. In addition, most importantly, Bayesian methods make it possible to rationally combine observed data with economically meaningful initial assumptions (priors). In practical terms observed data is combined with priors to generate a posterior distribution function. In fact, we derive the posterior distribution functions for all parameters in the model, leading to the posterior distribution function of GDP growth components.

The prior for the efficiency parameter is an asymmetric positive distribution. The rational behind this assumption is twofold. Firstly, this parameter measures the distance relatively to the production frontier so it should be positive. Secondly, there is a smaller probability of finding observations as we move further inside the production frontier. This assumption is common for the estimation of stochastic frontier functions but the specification of the asymmetric distribution remains an open question. We opted for a normal-gamma model (normal distribution of the residual component and gamma distribution for the efficiency component). Its relative advantages versus other alternatives, such as normal-half normal and normal-exponential models, are discussed in Greene (2000) and Tsionas (2000).

[1] For references on non-bayesian estimation methods of stochastic production functions see, for example, Aigner et al. (1977), Meeusen and der Broeck (1977) and Kumbhakar and Lovell (2004).

3.1 The model

The model considered for the decomposition of the GDP growth follows Koop et al. (1999), taking the form:

$$Y_{ti} = f_t\left(K_{ti}, L_{ti}\right)\tau_{ti}w_{ti}, \tag{1}$$

where Y_{ti}, K_{ti} and L_{ti} stand for the real output, the real capital stock and labour in period t $(t = 1,...,T)$ in country i $(i = 1,...,N)$, respectively. Furthermore, τ_{ti} $(0 < \tau_{ti} \leqslant 1)$ is the efficiency parameter and w_{ti} represents the measurement error in the identification and its stochastic nature. As mentioned above, the basic model assumes a flexible translog production function:

$$y_{ti} = x'_{ti}\beta_t + v_{ti} - u_{ti} \tag{2}$$

where:

$$x'_{ti} = \left(1, k_{ti}, l_{ti}, k_{ti}l_{ti}, k_{ti}^2, l_{ti}^2\right) \tag{3}$$

$$\beta_t = \left(\beta_{t1}, ..., \beta_{t6}\right)' \tag{4}$$

and lower case letters indicate natural logs of upper case letters. The logarithm of the measurement error v_{ti} is *iid* $N(0, \sigma_t^2)$ and the logarithm of the efficiency parameter is one sided to ensure that $\tau_{ti} = \exp\left(-u_{ti}\right)$ lies between zero and one. The prior for u_{ti} is taken to be a gamma function with a time specific mean λ_t.

The contribution of input endowment, technology change and efficiency change to GDP growth are defined in a simple way. The GDP growth rate in country i in period $t+1$ is:

$$y_{t+1,i} - y_{t,i} = \left(x'_{t+1,i}\beta_{t+1} - x'_{t,i}\beta_t\right) + \left(u_{t,i} - u_{t+1,i}\right), \tag{5}$$

where the first term includes technical progress and factor accumulation and the second term represents efficiency change. The first term can be further broken down as:

$$\frac{1}{2}\left(x_{t+1,i} + x_{ti}\right)'\left(\beta_{t+1} - \beta_t\right) + \frac{1}{2}\left(\beta_{t+1} + \beta_t\right)'\left(x_{t+1,i} - x_{ti}\right) \tag{6}$$

The technical change for a given level of inputs results from the first term of the previous equation and is defined as:

$$TC_{t+1,i} = \exp\left[\frac{1}{2}\left(x_{t+1,i} + x_{ti}\right)'\left(\beta_{t+1} - \beta_t\right)\right] \tag{7}$$

and the input change defined as the geometric average of two pure input change effects, relatively to the frontiers in consecutive periods:

$$IC_{t+1,i} = \exp\left[\frac{1}{2}\left(\beta_{t+1} + \beta_t\right)'\left(x_{t+1,i} - x_{ti}\right)\right] \tag{8}$$

The efficiency change is defined as:

$$EC_{t+1,i} = \exp(u_{ti} - u_{t+1,i}) = \frac{\tau_{t+1,i}}{\tau_{t,i}} \tag{9}$$

The average percentage changes in technology (ATC), input (AIC) and efficiency (AEC) are geometric averages and can be defined respectively as:

$$\begin{aligned}
ATC_i &= 100 * \left[\left(\prod_{t=1}^{T-1} TC_{t+1,i}\right)^{\frac{1}{T-1}} - 1\right] && (10)\\
AIC_i &= 100 * \left[\left(\prod_{t=1}^{T-1} IC_{t+1,i}\right)^{\frac{1}{T-1}} - 1\right] && (11)\\
AEC_i &= 100 * \left[\left(\prod_{t=1}^{T-1} EC_{t+1,i}\right)^{\frac{1}{T-1}} - 1\right] && (12)\\
&= 100 * \left[\left[\exp(u_{1,i} - u_{T,i})\right]^{\frac{1}{T-1}} - 1\right] && (13)
\end{aligned}$$

As previously mentioned, the structure of technological change can be modelled in different ways.[2] Parameters for technology may be different in each of the T periods or evolve either in a linear or quadratic way in each of the two 15-year periods. Furthermore, the linear trend model can be constrained to a constant returns to scale technology. Each of these alternatives presents advantages and limitations. The time specific model is very flexible but implies the sampling of numerous parameters, which is computationally heavy. The linear and quadratic trend models are less demanding in terms of parameters but impose some rigidity in the dynamics of technical progress. The quadratic trend is more flexible than the linear one, which makes it preferable if long periods of time are analysed. In turn, the linear trend

[2] See Koop et al. (1999) for a detailed discussion.

constrained to a constant returns technology imposes too much structure. Taking the set of alternatives, the linear trend model seems to offer the best compromise, with good results in terms of the in-sample fit and the ability to separate the components of TFP. Therefore:

$$\beta_t = \beta^* + t\beta^{**} \tag{14}$$

$$\sigma_t^2 = \ldots = \sigma_T^2 = \sigma^2 \tag{15}$$

Thus the model can be written as:

$$y = X^*\beta - u + v \tag{16}$$

with

$$y = \left(y_1'...y_T'\right), u = \left(u_1'...u_T'\right), v = (v_1...v_T)', \beta = \left(\beta^{*'}\beta^{**'}\right)', \tag{17}$$

where β is a 12×1 vector and:

$$X^* = \begin{bmatrix} X_1 & X_1 \\ . & . \\ X_t & tX_t \\ . & . \\ X_T & TX_T \end{bmatrix} \tag{18}$$

where X_t is a 49 (countries)$\times$6 vector. At this stage the full likelihood function of the model can be written as:

$$f_N^{TN}\left(y\left|X^*\beta - u, \sigma^2 I_{TN}\right.\right) p\left(\sigma^{-2}\right) p\left(\lambda^{-1}\right) \prod_{t=1}^{T}\prod_{i=1}^{N} f_G\left(u_{ti}\left|1, \lambda^{-1}\right.\right), \tag{19}$$

where f_N^{TN} stands for a multivariate $T \times N$ normal probability distribution function, f_G stands for a gamma probability distribution function and:

$$\begin{aligned} p\left(\lambda^{-1}\right) &= f_G\left(\lambda^{-1}\left|1, -\ln\left(\tau^*\right)\right.\right) \\ p\left(\sigma^{-2}\right) &= \sigma^2 \exp -\frac{10^{-6}}{2\sigma^2} \end{aligned}$$

The prior for λ^{-1} assumes a gamma distribution with the first parameter equal to 1 and second parameter equal to $-ln(\tau^*)^{-1}$ such that τ^* is the prior median efficiency. Typically τ^* is chosen based on a priori expectations for the median of the efficient distribution. However, in a very heterogeneous sample of countries, the existence of large deviations from the frontier increases the sum of errors and places the randomized algorithm that generates a sequence of posteriors - the sequential Gibbs sampler - in an unstable path. For the algorithm to accommodate such a sample, this has to be compensated by a low τ^*. We assume a starting point for τ^* near zero and check the posterior median efficiencies. For the first and second periods the posterior median efficiencies correspond to 0.85. As expected, the standard deviations of efficiency levels are high, corresponding to 0.15 and 0.14 p.p. in each period, respectively. In Koop et al. (1999) the set of countries is much more homogeneous (17 OECD countries) and τ^* is simply taken equal to 0.75. As for σ^{-2}, we assume the usual flat prior.

Given this prior structure, the posterior marginal distributions that compose the Gibbs sampler can be easily derived. The conditional for β is:

$$p\left(\beta \left| Data, u, \sigma^{-2}, \lambda^{-1}\right.\right) \sim f_N^{2J}\left(\beta \left| \widehat{\beta},\ \sigma^2\left(X^{*\prime}X^*\right)^{-1}\right.\right), \tag{20}$$

where

$$\widehat{\beta} = \left(X^{*\prime}X^*\right)^{-1} X^{*\prime}\left(y+u\right) \tag{21}$$

The conditional for σ^{-2} to be used in the Gibbs sampler is:

$$p\left(\sigma^{-2} \left| Data, \beta, u, \lambda^{-1}\right.\right) \sim f_G \left(\sigma^{-2} \left| \frac{n_0+TN}{2}, \frac{1}{2}\left[a_0+\left(y-X^*\beta+u\right)'\left(y-X^*\beta+u\right)\right]\right.\right) \tag{22}$$

Next, the conditional for u is a left truncated normal at zero:

$$p\left(u \left| Data, \beta, \sigma^{-2}, \lambda^{-1}\right.\right) \sim f_N^{TN}\left(u \left| X^*\beta - y - \frac{\sigma^2}{\lambda}\iota, \sigma^2 I_{NT}\right.\right) \prod_{t=1}^{T}\prod_{i=1}^{N} I(u_{it} \geqslant 0), \tag{23}$$

whose mean is forced to be higher or equal to zero in the algorithm and ι is a $TN \times 1$ vector of ones. Finally, the marginal posterior distribution for the λ^{-1} is:

$$p\left(\lambda^{-1} \left| Data, \beta, u, \sigma^{-2}\right.\right) = f_G\left(\lambda^{-1} \left| 1+TN, -\ln\left(\tau^*\right) + \sum_{t=1}^{T}\sum_{i=1}^{N} u_{it}\right.\right) \tag{24}$$

A final important element in the methodology is verification of regularity constraints regarding the elasticities of capital (EK_{ti}) and labour (EL_{ti}). Given the matricial formulation, these generic elements are:

$$EK_{ti} = (\beta_2^* + t\beta_8^{**}) + (\beta_4^* + t\beta_{10}^{**})l_{ti} + 2(\beta_5^* + t\beta_{11}^{**})k_{ti} \tag{25}$$

$$EL_{ti} = (\beta_3^* + t\beta_9^{**}) + (\beta_4^* + t\beta_{10}^{**})k_{ti} + 2(\beta_6^{**} + t\beta_{12}^{**})l_{ti} \tag{26}$$

Therefore, we only accept a set of posterior β parameters that translate into non-negative elasticities for all countries and periods.

The sequential Gibbs sampling algorithm defined by equations 20 to 24 was run with 1,020,000 iterations for each period, with a burn-in of the first 20,000 iterations to eliminate possible start-up effects (see Casella and George (1992)).

A very important feature in the methodology is to ensure that the algorithm converges to a stable distribution for each parameter, thus providing robust posterior estimates. In this context, we have computed the classic Geweke (1992) algorithm convergence criteria. Geweke's statistic is a convergence diagnostic for Markov chains based on a test for equality of the means of the initial and final parts of the chain, which has an asymptotically standard normal distribution. More specifically, if the two samples are drawn from the stationary distribution of the chain, the corresponding means should equalize. In our case, the Z scores for all parameters reject the probability of the difference between the means of the samples associated with the first and second half of the iterations to be different from zero.

We have also checked the minimum required number of iterations using the length control diagnostic for convergence suggested by Raftery and Lewis (1992, 1995), which is based on a criterion of accuracy to estimate a given quantile in the posterior distribution. This procedure calculates, for each variable separately, the number of iterations necessary to obtain a given accuracy interval with a given probability. In addition, it provides the minimum required sample size for a chain not to have correlation between consecutive samples. Moreover, the number of burn-in iterations to be discarded at the beginning of the chain is also calculated. In the paper, we applied this procedure for the median of coefficients, with an accuracy interval of 0.005 and a 95 percent probability, confirming that the number of iterations performed largely exceeds the minimum required.[3] The estimated parameters and the Geweke's Z scores are presented in Appendix A.

[3]The two diagnostics procedures mentioned above were computed using the R package 'coda' by Plummer et al. (2016), which is freely available on line.

3.2 Database

The data requirements comprise information for employment, capital stock and GDP from 1985 until 2014 for the set of 49 African countries considered. This information was collected from the latest vintage of the Penn World Table (version 8.0), whose methodology is presented in Feenstra et al. (2015). Growth accounting exercises depend upon reliable data and, when the aim is to estimate a stochastic production frontier, this data has to be comparable across countries. It is widely acknowledged that statistics for many African countries have limitations, especially going back in time. However, these problems extend also to other regions of the world. In spite of the international conventions governing national accounts compilation, there are country specific practices that tend to blur international comparisons. For example, the separation of nominal variations in price and volume is not equally computed by the national statistical authorities (Berndt and Triplett (1990)) and the compilation of value added for some services, notably those associated to general government, are also problematic.

The Penn World Table has set a standard for high quality in historical cross-country economic aggregates, thus it is suitable to provide an accurate insight into the size and contributions to income differences in Africa. The latest version of the database is more robust and has expanded the scope of information available relatively to the previous ones, notably in what concerns measures of physical capital. Feenstra et al. (2015) refers that prices collected across countries in benchmark years by the International Comparisons Program are used to construct the purchasing-power-parity (PPP) exchange rates that convert GDP at national prices into US dollars. Nevertheless, limitations remain in terms of cross-country price comparisons, especially between the richest and poorest countries, a point that is also made by Deaton and Heston (2010). Moreover, statistical agencies sometimes strongly revise GDP figures, amounting to more than 50 per cent in some developing countries (Jerven (2013)).

4 Results

The overall accuracy of the GDP growth estimates obtained from the Gibbs sampler is very good. The median absolute deviation between the observed and estimated average GDP growth rates for the set of 49 countries in the two periods considered is 0.8 and 0.9 p.p., respectively. As for the total contribution of inputs to average GDP growth rates, the accuracy is high. The interquartile ranges are 0.1 and 0.2 p.p. relatively to median total contributions of inputs of 2.2 and 4.4 p.p. in each period, respectively. The accuracy of the decomposition in the technology and efficiency blocks is lower. The median interquartile ranges are much larger than for the case of inputs, while the level of technology and efficiency contributions is much lower (see individual country results in Appendix B).

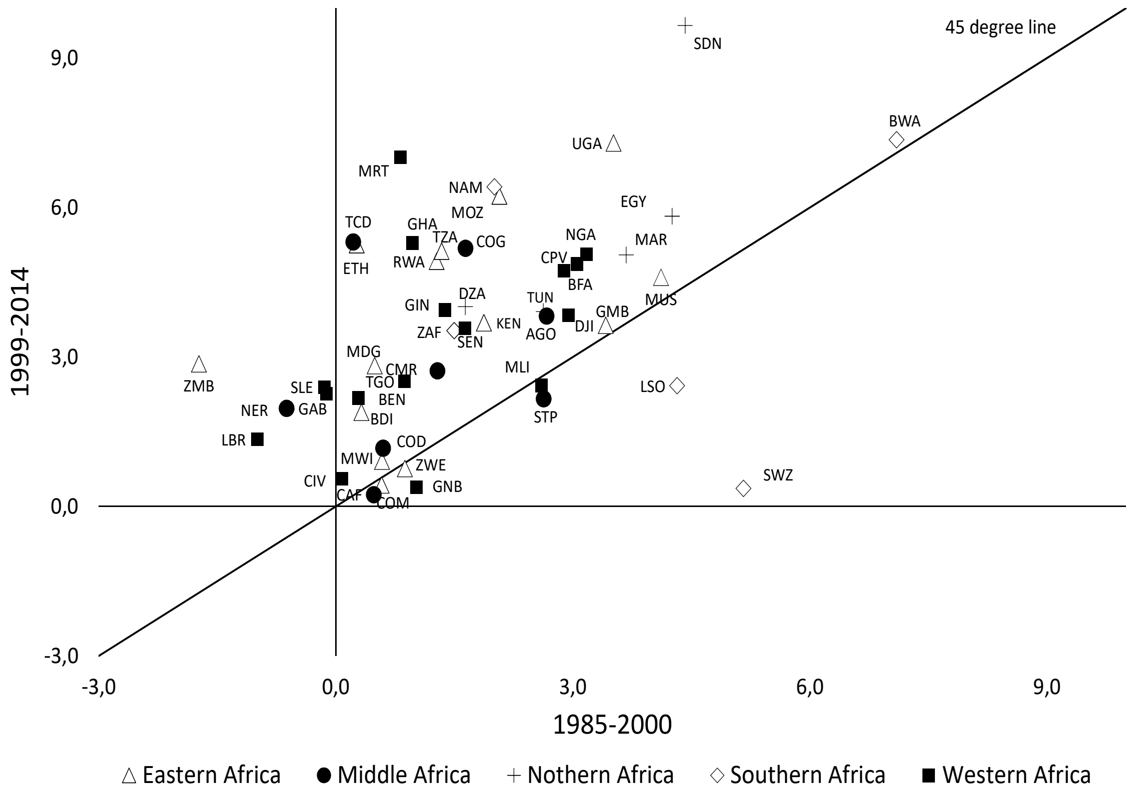
The rest of this section presents the results of the growth accounting decomposition, aiming to identify patterns across African countries and it is organized in four blocks. Firstly, as defined in equation 8, the contribution of inputs is computed as the geometric average relatively to the frontiers in consecutive years and capital and labour contributions are disentangled making use of their respective elasticities to GDP. Secondly, we present the contributions of efficiency and technological progress to GDP growth, as defined in equations 9 and 7, respectively. Thirdly, we discuss the change in the position of the frontiers, comparing the initial and final years of each period considered. Fourthly, the cases of South Africa, Nigeria and Egypt are highlighted.

4.1 Input accumulation

Figure 4 presents the contribution of capital accumulation to GDP growth in the two periods, identifying individual countries and associating the shape of markers to one of five African regions (Eastern, Middle, North, Southern and Western). The numbers underlying the figure, as well as the identification of country codes are presented in Appendix B. The first result that emerges is the very high contribution of capital accumulation to total GDP growth. In addition, these contributions clearly increased from the period 1985-2000 to 1999-2014 for the large majority of countries (41 out of 49), thus this pattern is present in the five African regions considered.

Theoretical growth models take the accumulation of capital as a major driver for economic development and growth accounting exercises empirically support this result. This feature also emerges in our context. The African reality is typically characterized by low levels of private and public savings, which highlights the importance of foreign direct investment (FDI) and external aid as sources of capital accumulation. As for FDI, although there is not a positive correlation with economic growth in all countries, it seems to be a driver for development. For example, the remarkable dynamism of the Congo in terms of FDI inflows correlates with high growth rates, while Gabon shows both a relatively lower GDP growth rate and a low level of FDI attractiveness (Nkoa (2013)). In what concerns external aid to development in African countries, although there is some heterogeneity, an upward trend is

Figure 4: Contribution of capital stock (percentage points)

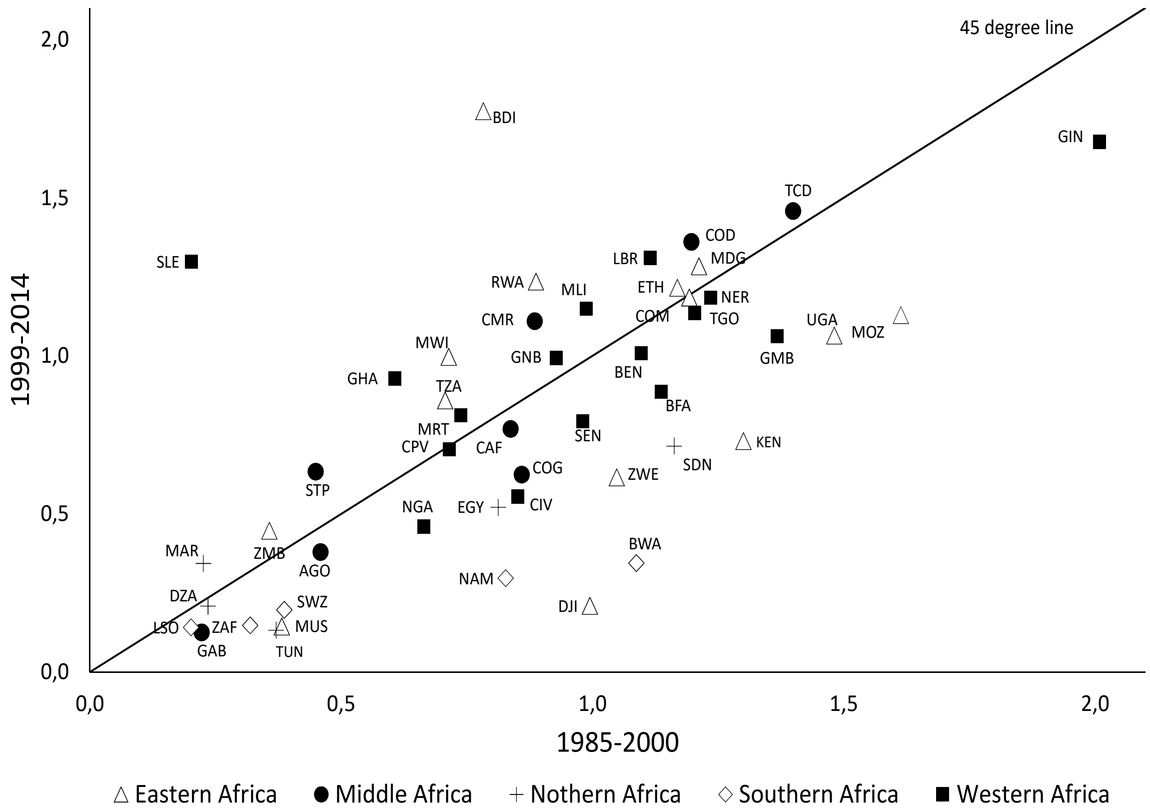


visible since the beginning of the century. This is compatible with the higher contribution of capital accumulation in the period 1999-2014 and it typically relates with improvements in basic infrastructure (ADB et al. (2016)). These results are compatible with firm level evidence. Harrison et al. (2014) refers that the key factors explaining Africa's disadvantage at the firm level are lack of infrastructure, access to finance, and political competition. In this vein, Eifert et al. (2008) uses firm survey data and highlights the role of indirect inputs' costs, notably infrastructure, on firm performance.

As for the labour input (Figure 5), the result is different from that of capital. Not only the level of contributions to GDP growth is smaller, but they are also relatively stable between the two periods considered. In what concerns the regional patterns, labour contributions of Southern African countries are amongst the smallest in the continent, while those in Eastern Africa nations stand among the highest, especially in the period 1999-2014.

The contribution of labour to GDP growth relates with demographic patterns and overall health conditions. As for demography developments, the population aged 15-64 as a share of total population in Africa has been the lowest in the world. It has only started to increase

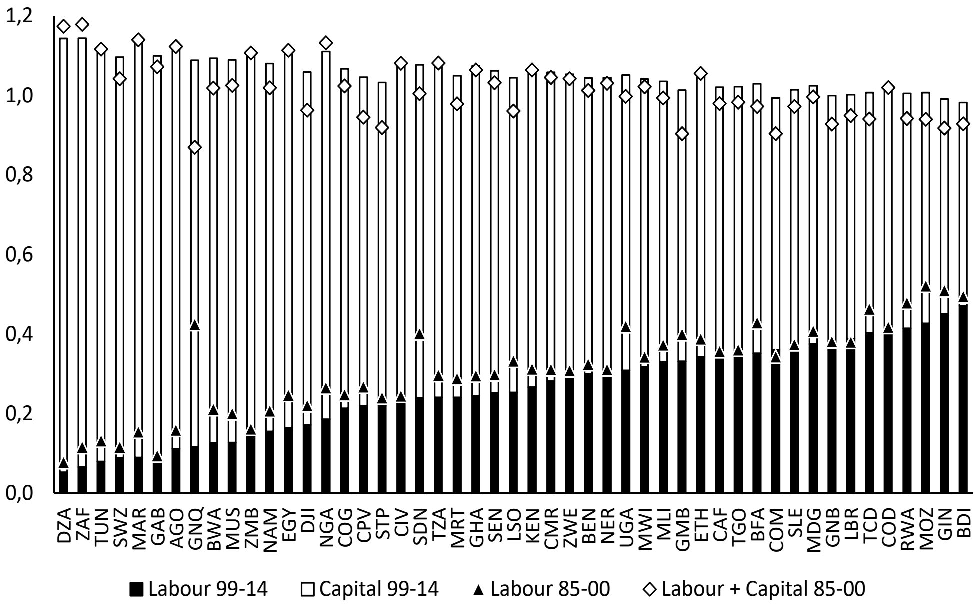
Figure 5: Contribution of employment (percentage points)



since the late eighties but at a rate lower than that observed in Asia and Latin America since the seventies. Nevertheless, a demographic dividend is foreseeable in the next decades as fertility rates are expected to decrease less in Africa than in other regions (Drummond et al. (2014)). Health conditions, notably the prevalence of HIV, have been a major issue in Africa in the last decades with a negative impact on the contribution of labour to economic growth. For example, Chicoine (2012) finds evidence that the epidemic has lowered employment in South Africa and Dixon et al. (2002) estimate that the pandemic has reduced average national economic growth rates by 2-4 percentage points a year across Africa.

The comparative contribution of capital and labour to GDP growth is driven by the elasticities of inputs estimated in the stochastic production function. Figure 6 presents these elasticities for the two periods considered, ranking countries according to labour elasticity in the latest years. The increase in capital-worker ratios makes it possible to incorporate more advanced technologies in the production process and possibly produce goods with higher value. Capital-intensive ICT sectors, whose activities have a deep impact on the production of most goods and services and whose relative price it is a good example of this "capital-

Figure 6: Elasticities of capital and labour in 1985-2000 and 1999-2014



Notes: The elasticities for capital and labour are functions of the posterior β parameters that compose the translog production function. Countries in the figure are ranked along the estimated labour elasticity in the period 1999-2014.

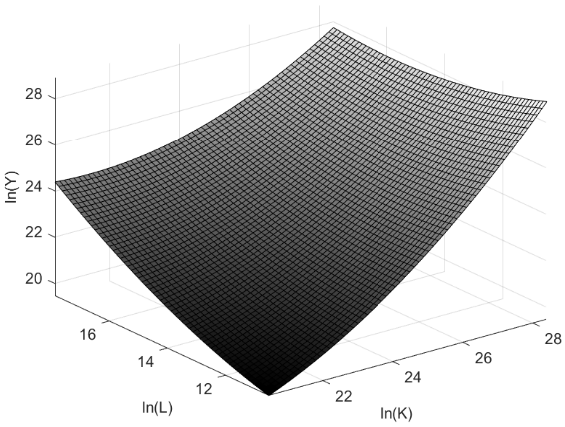
premium". For most African countries the labour elasticity is lower in the period 1999-2014, while capital elasticities increased over time. The ratio of capital and labour elasticities presents a cross-country distribution with a median close to 2 in the period 1985-2000 and equal to 3 in the period 1999-2014.

The results obtained for the elasticities of inputs are intrinsically associated with the shape of the production function. Figure 7 plots the three dimensional stochastic production frontier in 2014, considering the logarithm of K, L and Y in the axis. A relevant insight is that output tends to increase with more inputs but not in a uniform way. For example, higher labour in low capital segments increases output, while for high capital levels this is not visible. In addition, more capital in low labour segments sharply increases output.

4.2 Total factor productivity

The block of the growth accounting decomposition with lower precision is the breakdown of TFP developments into efficiency and technological changes. As for the contribution of efficiency developments to GDP growth, interpreted as changes in the distance to the frontier, results are summarized in Figure 8. Firstly, the levels of the contributions from efficiency

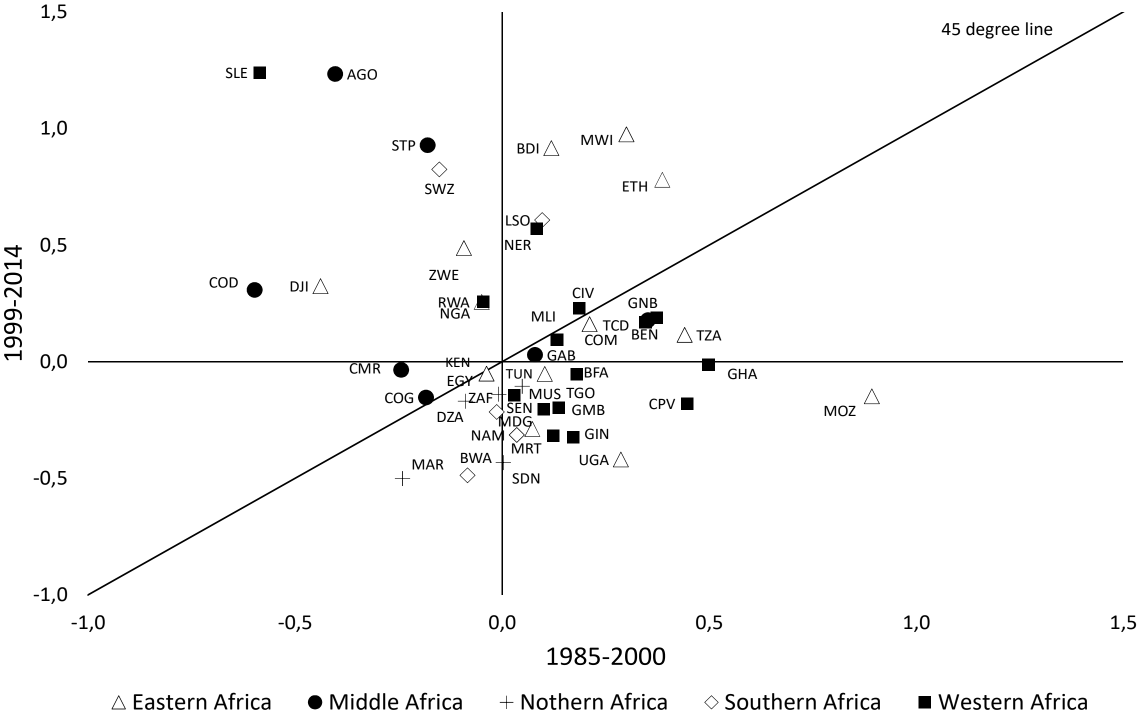
Figure 7: African stochastic production frontier in 2014



are generally low. Secondly, the majority of countries recorded positive contributions in the period 1985-2000, but only about half of those maintained this situation in the period 1999-2014, meaning that the structural reform may have lost momentum in some economies.

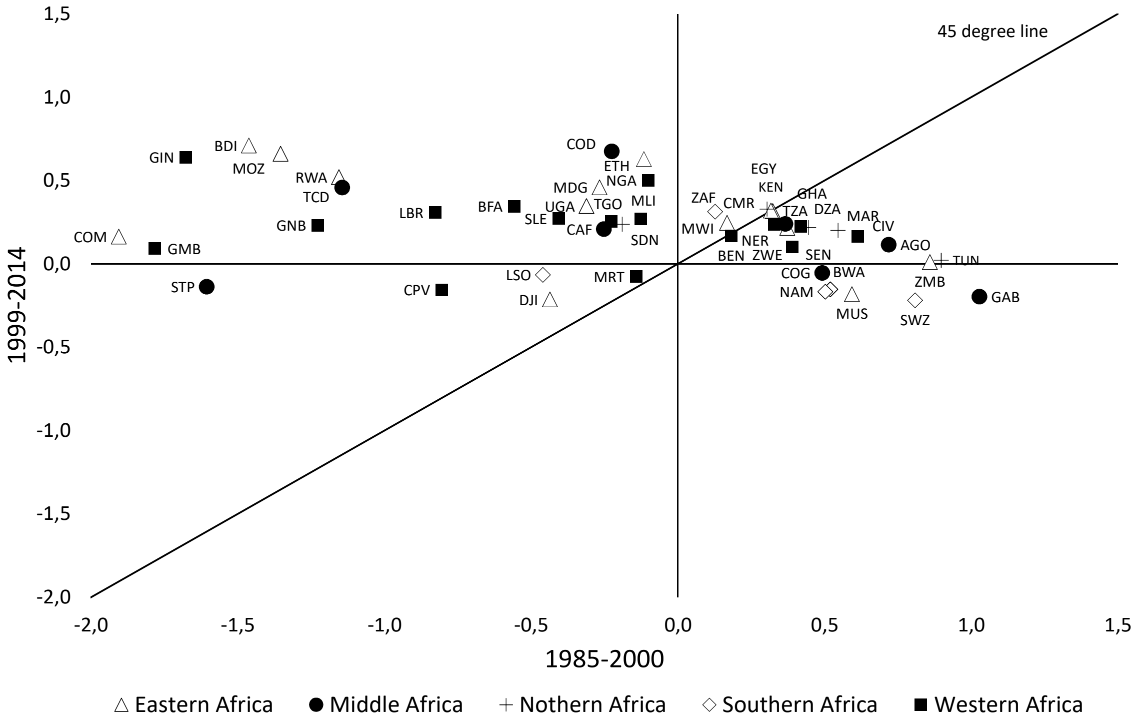
The estimation of the African stochastic production function makes it possible to asses how technological changes translate into GDP developments, depending on the positioning of countries in terms of the quantity of capital and labour inputs. Figure 9 presents the results obtained for the two periods considered. As for the case of technology, the contributions were also small when compared with those of capital and employment and they presented a larger dispersion in the 1986-2000 period. In addition, although most countries recorded positive contributions in the period 1999-2014, only 16 of them post positive contributions in both periods. For example, Eastern Africa countries like Mozambique, Burundi, Rwanda, Ethiopia and Madagascar recorded negative contributions in the period 1985-2000 but recovered in the following years. Conversely, countries like Botswana, Swaziland, Mauritius, Congo and Gabon, seem to have benefited from technological developments only in the initial period.

Figure 8: Contribution of efficiency developments (percentage points)



Note: Estimated contributions for Liberia and Zambia in 1999-2014 were large (2.4 and 1.8 p.p., respectively) and they are not presented in order to increase the visibility of the figure.

Figure 9: Contribution of technology developments (percentage points)



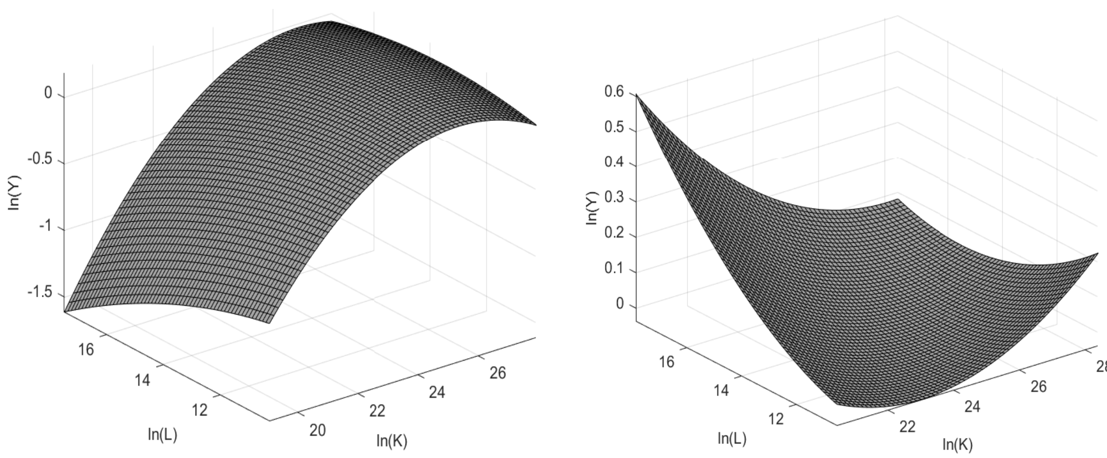
4.3 Change of production frontiers over time

The estimation of the stochastic production function considering a linear trend for technological progress makes it possible to compare the frontiers at the beginning and at the end of each period considered. Figure 10 presents the difference in GDP levels (vertical axis) between initial and final frontiers. The combined log levels of capital and labour define the log GDP that is possible to obtain with full efficiency at each moment and the difference between two moments in time reflects the change in the position and shape of the frontier. The difference from 1985 to 2000 (in panel a) shows contractions of GDP except for countries with intermediate employment levels and high capital. Conversely, in the period from 1999 to 2014 (in panel b) the frontier expanded in the segments of high employment and low capital and, to a lower extent, in high capital and low employment regions. These strong differences in the position of the frontiers over time, which may also be due to changes in the relative prices of goods produced, including commodities, are compatible with the opposing contributions from technology that are observed for many countries in the two periods.

4.4 Largest African economies

South Africa, Nigeria and Egypt are the three African countries with largest nominal GDP and they offer a good illustration of the main results presented above. The panels of Figure 11 present the contributions of inputs, efficiency, and technology in the two periods considered. These countries convey different realities. South Africa and Egypt are classified as advanced in fertility transition and urbanized, while Nigeria is considered a resource-based country. In

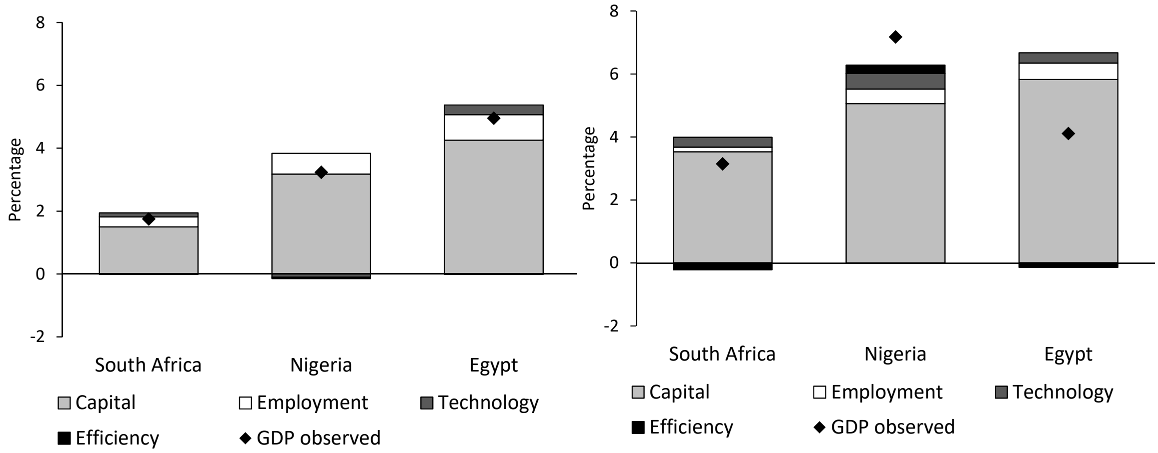
Figure 10: Change in the African stochastic production frontier over time



(a) Change from 1985 to 2000

(b) Change from 1999 to 2014

Figure 11: Growth accounting results for the three largest African economies



(a) 1985-2000

(b) 1999-2014

turn, South Africa is acknowledged as one of the countries in Africa where modernization has progressed more. Nevertheless, unemployment rates are very high, particularly among the youth, which contributes to high inequality in South Africa (OECD (2015)). Nigeria has been rapidly urbanising and its fast-growing cities also face increasing unemployment and income inequality, while Egypt continues to work towards achieving sustainable cities and structural transformation. However, Egypt's high population growth also poses major challenges for the sustainability of urban growth (ADB et al. (2016)).

Despite their differences, the strong contribution of capital accumulation to GDP growth is clearly dominant in the two periods in the three economies. In addition, the contribution from employment was positive in the first period, though very small in South Africa. In the 1999-2014 period, this contribution was reduced in Nigeria and Egypt. As for TFP developments, although the significance of estimates is lower as interquartile ranges are wider, in the second period, the contribution of efficiency was marginally positive in Nigeria and marginally negative in South Africa and Egypt. Finally, technological progress gave a positive contribution to GDP growth in the three countries in the final period.

5 Concluding remarks

In this paper, we conduct a growth accounting exercise based on the estimation of a dynamic stochastic production frontier for Africa. The exercise conveys a good overall fit as the sum of different contributions is not distant from observed GDP growth, though quality lowers when it comes to splitting TFP developments into efficiency and technological contributions.

One of the important results of the paper is that the contribution of capital accumulation to recent economic growth in Africa is very important. The ratio of capital and labour elasticities presents a cross-country distribution with a median close to 2 in the period 1985-2000 and equal to 3 in the period 1999-2014. Therefore, the ability to increase domestic savings rates, attract FDI, and maintain external aid is very important to sustain the recent good performance of GDP in Africa. In addition, the contribution of labour input was mildly positive and stable in the two periods, reflecting the fact that the demographic dividend in African growth is still to be materialized. As referred in The Global Human Capital Report (2017), the region will remain relatively young for decades making investment in education and in the creation of work opportunities beyond routine and lower-skilled occupations crucial to explore its human capital potential in the labour market. The contributions of technological progress to GDP growth are small when compared with those of capital and labour and mostly positive in the most recent period. Moreover, the majority of countries recorded positive contributions from efficiency in the period 1985-2000 but only about half of them maintained this situation in the period 1999-2014, meaning that the reform may have lost momentum in some economies.

The opportunities for a sustainable economic growth in Africa exist but this will require persistent efforts from policy-makers and firms. The continuation of a good economic performance is key for improving the well-being of African populations and also for the world economy in general. A thriving African economy will have a positive spillover in a world plagued by low productivity growth. In this context, further research on the drivers of African growth is necessary and cross-country studies are as important as those that focus on the impact of local reforms. Growth accounting literature is a useful tool in this research agenda. In particular, taking explicitly into account the quality and the characteristics of human capital and stocks of physical capital, as well as the institutional features of the economies, stands as a promising avenue for future research.

References

ADB, OECD and UNDP (2016), The African Economic Outlook, Technical report, African Development Bank, OECD Development Centre and United Nations Development Programme.

Aigner, D., Lovell, C. and Schmidt, P. (1977), 'Formulation and estimation of stochastic frontier production function models', *Journal of Econometrics* (6), 21–37.

Annunziata, M., Johnson, T. and Kramer, S. (2014), Growth and Governance in Africa: Towards a Sustainable Success Story, Report, GE Ideas Lab.

Arbache, J., Go, D. S. and Page, J. (2008), Is Africa's economy at a turning point?, Policy Research Working Paper Series 4519, The World Bank.

Barro, R. (1991), 'Economic growth in a cross section of countries', *Quarterly Journal of Economics* **106**, 407–433.

Basu, W. and Weil, D. (1998), 'Appropriate technology and growth', *Quarterly Journal of Economics* **113**, 1025–1054.

Baumol, W. (1986), 'Productivity growth, convergence, and welfare: What the long-run data show', *American Economic Review* **76**(5), 1072–85.

Berndt, E. and Triplett, J. (1990), *Fifty Years of Economic Measurement*, University of Chicago Press.

Casella, G. and George, E. (1992), 'Explaining the Gibbs sampler', *The American Statistician* (46), 167–174.

Chicoine, L. (2012), 'AIDS mortality and its effect on the labor market: Evidence from South Africa', *Journal of Development Economics* **98**(2), 256–269.

Deaton, A. and Heston, A. (2010), 'Understanding PPPs and PPP-Based National Accounts', *American Economic Journal: Macroeconomics* **2**(4), 1–35.

Dixon, S., McDonald, S. and Roberts, J. (2002), 'The impact of HIV and AIDS on Africa's economic development', *BMJ* **324**(26).

Drummond, P., Thakoor, V. and Yu, S. (2014), Africa Rising; Harnessing the Demographic Dividend, IMF Working Papers 14/143, International Monetary Fund.

Eifert, B., Gelb, A. and Ramachandran", V. (2008), 'The cost of doing business in africa: Evidence from enterprise survey data', *World Development* **36**(9), 1531–1546.

Erten, B. and Ocampo, J. (2013), 'Super cycles of commodity prices since the mid-nineteenth century', *World Development* (44), 14–30.

Feenstra, R. C., Inklaar, R. and Timmer, M. P. (2015), 'The Next Generation of the Penn World Table', *American Economic Review* **105**(10), 3150–82.

Geweke, J. (1992), Evaluating the accuracy of sampling based approaches to the calculation of posterior moments, *in* J. Bernardo, J. Berger, A. Dawid and A. Smith, eds, 'Bayesian Statistics 4: Proceedings of the Fourth Valencia International Meeting', Oxford Clarendon Press.

Greene, W. (2000), 'Simulated likelihood estimation of the normal-gamma stochastic frontier function', *Quarterly Journal of Economics* **113**, 1025–1054.

Griffin, J. and Steel, M. (2004), 'Semiparametric Bayesian inference for stochastic frontier models', *Journal of Econometrics* (123), 121–152.

Harchaoui, T. and Ungor, M. (2018), 'The lion on the move towards the world frontier: Catching up or remaining stuck?', *Journal of African Economies* **27**(3), 251–273.

Harrison, A. E., Lin, J. Y. and Xu, L. C. (2014), 'Explaining africa?s (dis)advantage', *World Development* **63**, 59–77.

Jerven, M. (2013), 'Comparability of GDP estimates in Sub-Saharan Africa: The Effect of Revisions in Sources and Methods Since Structural Adjustment', *Review of Income and Wealth* **59**, S16–S36.

King, A. and Ramlogan-Dobson, C. (2015), 'Is africa actually developing?', *World Development* **66**, 598 – 613.

Koop, G., Osiewalski, J. and Steel, M. (1999), 'The components of output growth: A stochastic frontier analysis', *Oxford Bulletin of Economics and Statistics* **61**(4), 455–487.

Koop, G., Osiewalski, J. and Steel, M. (2000), 'Modelling the sources of output growth in a panel of countries', *Journal of Business & Economic Statistics* **18**(3), 284–299.

Kumbhakar, S. C. and Lovell, C. (2004), *Stochastic Frontier Analysis*, Cambridge University Press.

Lucas, R. (1988), 'On the mechanics of economic development', *Journal of Monetary Economics* **22**, 3–42.

McMillan, M. S. and Harttgen, K. (2014), What is driving the "African Growth Miracle"?, NBER Working Papers 20077, National Bureau of Economic Research, Inc.

Meeusen, W. and der Broeck, V. (1977), 'Efficiency estimation from Cobb-Douglas production functions with composed error', *International Economic Review* (18), 435–452.

Nkoa, E. (2013), 'Does foreign direct investment improve economic growth in CEMAC countries?', *European Journal of Business and Economics* .

OECD (2015), OECD Economic Surveys - South Africa, Report, OECD.

Plummer, M., Best, N., Cowles, K., Vines, K., Sarkar, D., Bates, D., Almond, R., Magnusson, A. and Magnusson, A. (2016), Package 'coda', Report, CRAN.

Raftery, A. and Lewis, S. (1992), 'One long run with diagnostics: Implementation strategies for Markov Chain Monte Carlo', *Statistical Science* (7), 493–497.

Raftery, A. and Lewis, S. (1995), The number of iterations, convergence diagnostics and generic metropolis algorithms, *in* 'In Practical Markov Chain Monte Carlo (W.R. Gilks, D.J. Spiegelhalter and', Chapman and Hall, pp. 115–130.

Rodrik, D. (2014), An African Growth Miracle?, NBER Working Papers 20188, National Bureau of Economic Research, Inc.

Romer, P. (1986), 'Increasing returns and long-run growth', *Journal of Political Economy* **94**(5), 1002–1037.

Romer, P. (1990), 'Endogenous technological change', *Journal of Political Economy* **98**(5), 71–102.

Sala-Martin, X. (1997), 'I just ran 2 million regressions', *American Economic Review* **87**(2), 178–183.

Solow, R. (1956), 'A contribution to the theory of economic growth', *Quarterly Journal of Economics* **70**, 65–34.

Solow, R. (1957), 'Technical change and the aggregate production function', *Review of Economics and Statistics* **39**, 312–320.

Temple, J. (2006), ‘Aggregate production functions and growth economics’, *International Review of Applied Economics* **20**(3), 301–317.

Tsionas, E. (2000), ‘Full likelihood inference in normal-gamma stochastic frontier models’, *Journal of Productivity Analysis* **13**, 183–205.

Zedillo, E., Cattaneo, O. and Wheeler, H. (2015), *Africa at a Fork in the Road: Taking Off or Disappointment Once Again?*, Yale Center for the Study of Globalization.

A Parameters and diagnostics

Period 1985-2000

	Average	Median	IQR	z-score	p-value
β_1	28.714	28.917	7.876	0.70	0.49
β_2	-2.187	-2.214	0.752	-0.51	0.61
β_3	1.488	1.515	0.560	0.01	0.99
β_4	-0.103	-0.105	0.032	-0.33	0.74
β_5	0.089	0.090	0.021	0.43	0.67
β_6	0.046	0.049	0.023	0.49	0.62
β_7	-0.997	-1.010	0.906	-0.80	0.42
β_8	0.081	0.083	0.084	0.69	0.49
β_9	-0.006	-0.006	0.053	-0.07	0.95
$\beta_1 0$	0.001	0.001	0.003	1.43	0.15
$\beta_1 1$	-0.002	-0.002	0.002	-1.06	0.29
$\beta_1 2$	-0.001	-0.001	0.002	-1.79	0.07
λ	0.241	0.240	0.021	0.41	0.68
σ	0.203	0.203	0.017	-0.24	0.81

Period 1999-2014

	Average	Median	IQR	z-score	p-value
β_1	12.441	12.437	8.246	1.04	0.30
β_2	-0.888	-0.890	0.744	-1.03	0.30
β_3	1.433	1.454	0.384	0.15	0.88
β_4	-0.090	-0.092	0.026	-0.09	0.93
β_5	0.061	0.061	0.019	0.82	0.41
β_6	0.035	0.037	0.020	0.00	1.00
β_7	0.169	0.169	0.831	-1.66	0.10
β_8	-0.019	-0.019	0.075	1.22	0.22
β_9	0.009	0.009	0.039	0.41	0.68
$\beta_1 0$	-0.001	-0.001	0.002	-0.10	0.92
$\beta_1 1$	0.001	0.001	0.002	-0.57	0.57
$\beta_1 2$	0.000	0.000	0.002	0.00	1.00
λ	0.238	0.237	0.022	0.38	0.71
σ	0.110	0.110	0.010	0.58	0.56

B Detailed growth accounting by country

Results for period 1985-2000

Code	Country	GDP			Input		K	L	Technology		Efficiency	
		Obs.	Est.	IQR	Est.	IQR	Est.	Est.	Est.	IQR	Est.	IQR
AGO	Angola	1.8	3.4	2.6	3.1	0.1	2.7	0.5	0.7	1.0	-0.4	2.5
BDI	Burundi	0.0	-0.2	2.8	1.1	0.1	0.3	0.8	-1.5	1.2	0.1	2.6
BEN	Benin	4.0	2.5	2.3	2.0	0.1	0.9	1.1	0.2	0.7	0.4	2.2
BFA	Burkina Faso	4.4	3.6	2.2	4.0	0.1	2.9	1.1	-0.6	0.8	0.2	2.0
BWA	Botswana	7.3	8.6	1.7	8.2	0.2	7.1	1.1	0.5	0.9	-0.1	1.3
CAF	Cent. African Rep.	1.4	1.2	2.9	1.3	0.0	0.5	0.8	-0.3	0.7	0.1	2.8
CIV	Côte d'Ivoire	2.5	1.7	2.2	0.9	0.1	0.1	0.9	0.6	0.8	0.2	2.0
CMR	Cameroon	-0.1	2.3	1.6	2.2	0.1	1.3	0.9	0.4	0.7	-0.2	1.4
COD	D.R. of the Congo	-3.9	1.0	2.1	1.8	0.2	0.6	1.2	-0.2	1.1	-0.6	1.7
COG	Congo	0.8	2.8	1.6	2.5	0.1	1.6	0.9	0.5	0.8	-0.2	1.4
COM	Comoros	1.3	0.1	2.4	1.8	0.1	0.6	1.2	-1.9	1.5	0.2	1.8
CPV	Cabo Verde	5.6	3.4	2.3	3.8	0.2	3.1	0.7	-0.8	1.2	0.4	2.0
DJI	Djibouti	1.2	3.5	2.4	4.4	0.2	3.4	1.0	-0.4	1.3	-0.4	2.1
DZA	Algeria	1.5	2.2	2.4	1.9	0.1	1.6	0.2	0.4	1.7	-0.1	1.6
EGY	Egypt	5.0	5.4	1.5	5.1	0.2	4.3	0.8	0.3	1.1	0.0	1.0
ETH	Ethiopia	2.6	1.7	3.2	1.4	0.2	0.3	1.2	-0.1	1.4	0.4	3.0
GAB	Gabon	1.4	0.7	1.9	-0.4	0.2	-0.6	0.2	1.0	1.2	0.1	1.4
GHA	Ghana	4.4	2.5	2.4	1.6	0.1	1.0	0.6	0.4	0.7	0.5	2.3
GIN	Guinea	3.9	1.9	1.9	3.4	0.1	1.4	2.0	-1.7	1.3	0.2	1.2
GMB	Gambia	3.3	2.6	2.0	4.3	0.2	2.9	1.4	-1.8	1.2	0.1	1.5
GNB	Guinea-Bissau	2.5	1.1	2.4	1.9	0.1	1.0	0.9	-1.2	1.0	0.3	2.2
GNQ	Equatorial Guinea	12.7	11.5	2.2	14.0	1.4	12.7	1.3	-2.7	1.8	0.3	1.5
KEN	Kenya	3.0	3.5	1.8	3.2	0.1	1.9	1.3	0.3	0.8	0.0	1.6
LBR	Liberia	-2.6	-1.2	2.8	0.1	0.1	-1.0	1.1	-0.8	0.8	-0.5	2.7
LSO	Lesotho	4.3	4.2	2.5	4.5	0.2	4.3	0.2	-0.5	0.8	0.1	2.4
MAR	Morocco	3.0	4.2	2.5	3.9	0.2	3.7	0.2	0.5	1.2	-0.2	2.2
MDG	Madagascar	2.0	1.5	1.7	1.7	0.1	0.5	1.2	-0.3	0.8	0.1	1.5
MLI	Mali	4.2	3.6	2.1	3.6	0.1	2.6	1.0	-0.1	0.7	0.1	1.9
MOZ	Mozambique	5.9	3.2	3.0	3.7	0.2	2.1	1.6	-1.4	1.5	0.9	2.8
MRT	Mauritania	2.8	1.5	1.6	1.6	0.1	0.8	0.7	-0.1	0.8	0.1	1.3
MUS	Mauritius	5.8	5.2	1.9	4.5	0.1	4.1	0.4	0.6	0.9	0.1	1.6
MWI	Malawi	2.5	1.8	3.0	1.3	0.1	0.6	0.7	0.2	0.7	0.3	2.9
NAM	Namibia	3.6	3.4	1.7	2.8	0.1	2.0	0.8	0.5	0.9	0.0	1.4
NER	Niger	1.6	1.5	3.3	1.1	0.1	-0.1	1.2	0.3	0.7	0.1	3.2
NGA	Nigeria	3.2	3.7	2.5	3.8	0.2	3.2	0.7	-0.1	1.7	0.0	1.8
RWA	Rwanda	0.5	1.0	2.2	2.2	0.1	1.3	0.9	-1.2	1.1	0.0	1.8
SDN	Sudan (Former)	5.2	5.4	1.3	5.6	0.2	4.4	1.2	-0.2	0.8	0.0	1.0
SEN	Senegal	3.1	3.0	2.1	2.6	0.1	1.6	1.0	0.4	0.7	0.0	1.9
SLE	Sierra Leone	-4.3	-0.9	2.1	0.1	0.1	-0.1	0.2	-0.4	0.7	-0.6	2.0
STP	S. Tomé & Princípe	0.6	1.3	3.2	3.1	0.2	2.6	0.4	-1.6	2.1	-0.2	2.8
SWZ	Swaziland	5.3	6.2	2.6	5.5	0.2	5.2	0.4	0.8	1.2	-0.2	2.3
TCD	Chad	3.1	0.8	2.0	1.6	0.1	0.2	1.4	-1.1	1.0	0.4	1.7
TGO	Togo	2.0	1.4	2.2	1.5	0.1	0.3	1.2	-0.2	0.7	0.1	2.1
TUN	Tunisia	4.0	3.9	2.3	3.0	0.1	2.6	0.4	0.9	1.0	0.0	2.0
TZA	Tanzania	3.9	2.8	2.9	2.0	0.1	1.3	0.7	0.3	0.9	0.4	2.9
UGA	Uganda	6.3	5.0	2.1	5.0	0.2	3.5	1.5	-0.3	0.9	0.3	1.9
ZAF	South Africa	1.8	1.9	2.6	1.8	0.1	1.5	0.3	0.1	1.8	0.0	1.9
ZMB	Zambia	1.6	0.2	3.5	-1.4	0.1	-1.7	0.4	0.9	0.9	0.7	3.5
ZWE	Zimbabwe	1.8	2.2	2.7	1.9	0.1	0.9	1.0	0.4	0.7	-0.1	2.7

Results for period 1999-2014

Code	Country	GDP			Input		K	L	Technology		Efficiency	
		Obs.	Est.	IQR	Est.	IQR	Est.	Est.	Est.	IQR	Est.	IQR
AGO	Angola	7.0	5.6	2.9	4.2	0.1	3.8	0.4	0.1	0.8	1.2	2.9
BDI	Burundi	7.1	5.3	2.5	3.7	0.2	1.9	1.8	0.7	1.2	0.9	2.4
BEN	Benin	4.3	3.9	2.0	3.5	0.1	2.5	1.0	0.2	0.6	0.2	2.0
BFA	Burkina Faso	5.5	5.9	2.0	5.6	0.1	4.7	0.9	0.3	0.6	-0.1	1.9
BWA	Botswana	4.4	7.1	1.7	7.7	0.2	7.4	0.3	-0.2	0.7	-0.5	1.6
CAF	Cent. African Rep.	-1.5	-0.2	3.1	1.0	0.1	0.2	0.8	0.2	0.6	-1.4	3.1
CIV	Côte d'Ivoire	2.2	1.5	1.8	1.1	0.1	0.6	0.6	0.2	0.6	0.2	1.7
CMR	Cameroon	3.8	4.0	1.6	3.8	0.1	2.7	1.1	0.2	0.6	0.0	1.5
COD	D.R. of the Congo	4.6	3.5	2.0	2.5	0.1	1.2	1.4	0.7	1.1	0.3	1.7
COG	Congo	4.7	5.6	1.7	5.8	0.1	5.2	0.6	-0.1	0.7	-0.2	1.5
COM	Comoros	2.7	1.9	2.1	1.6	0.1	0.4	1.2	0.2	1.5	0.2	1.4
CPV	Cabo Verde	4.4	5.2	1.9	5.6	0.2	4.9	0.7	-0.2	0.9	-0.2	1.7
DJI	Djibouti	4.3	4.0	2.6	3.8	0.2	3.6	0.2	-0.2	1.1	0.3	2.5
DZA	Algeria	3.6	4.3	2.2	4.2	0.2	4.0	0.2	0.2	1.2	-0.2	1.9
EGY	Egypt	4.1	6.5	1.3	6.3	0.2	5.8	0.5	0.3	0.9	-0.1	0.8
ETH	Ethiopia	8.6	7.9	2.9	6.5	0.2	5.3	1.2	0.6	1.1	0.8	2.9
GAB	Gabon	2.1	1.9	1.4	2.1	0.1	2.0	0.1	-0.2	0.8	0.0	1.1
GHA	Ghana	6.2	6.4	2.1	6.2	0.1	5.3	0.9	0.2	0.6	0.0	2.0
GIN	Guinea	2.6	5.9	1.5	5.6	0.2	3.9	1.7	0.6	1.0	-0.3	1.1
GMB	Gambia	3.5	4.8	1.7	4.9	0.2	3.8	1.1	0.1	0.8	-0.2	1.4
GNB	Guinea-Bissau	2.3	1.8	2.0	1.4	0.1	0.4	1.0	0.2	1.0	0.2	1.8
GNQ	Equatorial Guinea	13.4	16.9	1.5	17.4	0.5	17.0	0.4	-0.2	0.8	-0.3	1.2
KEN	Kenya	4.3	4.7	1.6	4.4	0.1	3.7	0.7	0.3	0.6	-0.1	1.5
LBR	Liberia	8.1	5.4	2.9	2.7	0.1	1.4	1.3	0.3	0.8	2.4	2.9
LSO	Lesotho	4.1	3.1	2.5	2.6	0.1	2.4	0.1	-0.1	0.7	0.6	2.5
MAR	Morocco	4.3	5.1	2.9	5.4	0.2	5.0	0.3	0.2	1.0	-0.5	2.9
MDG	Madagascar	2.7	4.3	1.6	4.1	0.1	2.8	1.3	0.5	0.7	-0.3	1.5
MLI	Mali	4.2	3.9	1.7	3.6	0.1	2.4	1.1	0.3	0.6	0.1	1.6
MOZ	Mozambique	7.2	7.9	2.2	7.4	0.3	6.2	1.1	0.7	1.0	-0.1	2.1
MRT	Mauritania	4.6	7.4	1.4	7.8	0.2	7.0	0.8	-0.1	0.7	-0.3	1.2
MUS	Mauritius	4.1	4.5	1.6	4.7	0.1	4.6	0.1	-0.2	0.8	-0.1	1.4
MWI	Malawi	4.3	3.1	2.8	1.9	0.1	0.9	1.0	0.2	0.6	1.0	2.8
NAM	Namibia	4.3	6.2	1.6	6.7	0.1	6.4	0.3	-0.2	0.7	-0.3	1.4
NER	Niger	4.6	4.3	3.3	3.4	0.1	2.3	1.2	0.2	0.6	0.6	3.3
NGA	Nigeria	7.2	6.3	2.0	5.5	0.2	5.1	0.5	0.5	1.3	0.3	1.6
RWA	Rwanda	7.6	6.9	1.9	6.2	0.3	4.9	1.2	0.5	0.8	0.3	1.7
SDN	Sudan (Former)	5.1	10.2	1.2	10.4	0.2	9.7	0.7	0.2	0.6	-0.4	1.1
SEN	Senegal	3.8	4.3	2.1	4.4	0.1	3.6	0.8	0.1	0.6	-0.1	2.0
SLE	Sierra Leone	8.9	5.2	2.2	3.7	0.1	2.4	1.3	0.3	0.6	1.2	2.2
STP	S. Tomé & Princípe	4.6	3.6	3.0	2.8	0.2	2.2	0.6	-0.1	1.7	0.9	3.0
SWZ	Swaziland	2.6	1.2	2.6	0.6	0.1	0.4	0.2	-0.2	0.9	0.8	2.5
TCD	Chad	8.7	7.4	1.4	6.8	0.3	5.3	1.5	0.5	0.7	0.2	1.1
TGO	Togo	2.8	3.4	2.1	3.3	0.1	2.2	1.1	0.3	0.6	-0.2	2.1
TUN	Tunisia	3.6	4.0	2.3	4.0	0.1	3.9	0.1	0.0	0.8	-0.1	2.2
TZA	Tanzania	6.3	6.4	3.0	6.0	0.2	5.1	0.9	0.3	0.7	0.1	3.0
UGA	Uganda	6.6	8.3	1.9	8.4	0.2	7.3	1.1	0.3	0.6	-0.4	1.9
ZAF	South Africa	3.1	3.8	2.4	3.7	0.1	3.5	0.1	0.3	1.4	-0.2	2.1
ZMB	Zambia	6.7	5.1	3.1	3.3	0.1	2.9	0.4	0.0	0.7	1.8	3.1
ZWE	Zimbabwe	2.8	2.1	2.6	1.4	0.1	0.8	0.6	0.2	0.6	0.5	2.6