Economic Modelling 44 (2015) 171–179

Contents lists available at ScienceDirect

Economic Modelling

journal homepage: www.elsevier.com/locate/ecmod

# What drives national efficiency in sub-Saharan Africa

Michael Danquah [a], Bazoumana Ouattara [b,*]

[a] Department of Economics, University of Ghana, P. O. Box LG 57, Legon, Accra, Ghana
[b] IDPM, 1st Floor Arthur Lewis Building, University of Manchester, Oxford Road, Manchester M13 9PL, United Kingdom

ARTICLE INFO

*Article history:*
Accepted 14 October 2014
Available online 5 November 2014

*Keywords:*
National efficiency
Stochastic frontier model
Sub-Saharan Africa

ABSTRACT

In this paper, we use stochastic frontier analysis to examine whether differences in the transfer and absorption of technology help to explain cross-country differences in national efficiency levels in sub-Saharan Africa over the period 1970–2010. We find that trade policy on openness, machinery imports, stock of R&D, landlockedness and quality of institutions play a significant and quantitatively important role in explaining the differences in efficiency scores in SSA. Human capital, however, has an insignificant effect on efficiency.



## 1. Introduction

Over the past four decades the growth performance of sub-Saharan African (SSA) countries has been poor compared to that of other developing countries. In particular, the average sub-Saharan African per capita real GDP growth has hardly exceeded 2%, whilst East Asia and Pacific countries have been experiencing impressive growth rates in the ranges of 4 to 8%.[1] The poor SSA growth performance is worrisome given that the region needs to grow at a much higher level in order to achieve the Millennium Development Goals (MDGs) target of halving the fraction of population living below $1 per day by 2015. It is estimated that the average annual growth performance in the region at 3.5% during 1997–2002 (considered as a growth recovery period) is even less than half of the estimated growth needed to achieve the poverty reduction goal of the MDGs (Tahari et al., 2004). A large body of studies (Berthelemy and Söderling, 2002; Collins and Bosworth, 2003; Fosu, 2009; Hoeffler, 2002; Ndulu and O'Connell, 2000, 2003; Tahari et al., 2004) suggest that low total factor productivity (TFP) growth is the main impediment to the poor SSA growth performance.[2] Current quantifiable progress reports of the MDGs and Poverty Reduction Strategy Papers (PRSPs) in most SSA countries still indicate that a significant boost in TFP growth (i.e. improvements in efficiency and technical progress)[3] is required in order to double the average annual growth rate to achieve the targets set out in these programs. What is more, differences in efficiency explain most of the differences in productivity amongst countries (Jerzmanowski, 2007; Prescott, 1998). In other words, the low levels of output per worker in many countries are largely attributed to the countries' efficiency in using available resources and technology.

There have been a handful of studies estimating the technical efficiency of countries and evaluating its determinants (see Mastromarco, 2002; Milner and Weyman-Jones, 2003; Kneller and Stevens, 2006; Christopoulos, 2007; Mastromarco and Ghosh, 2008; Henry et al., 2009; amongst others). However, most of these studies are focused on OECD countries and a few on developing countries as a whole (see Christopoulos, 2007; Henry et al., 2009; Mastromarco and Ghosh, 2008).

This study contributes to the literature in two different ways. Firstly, the paper focuses on SSA countries, which have witnessed poor growth performance for decades. Secondly, the paper probes deeper into the factors affecting national efficiency of SSA countries by robustly examining an expanded and suitable set of relevant explanatory variables capturing technology transfer and absorptive capacity—in particular, human capital, stock of R&D (absorptive capacity), machinery imports, trade policy openness, landlockedness and institutions. To achieve this, we use a non-monotonic version of the complex time 'decay' model of Battese and Coelli (1995),[4] which allows us to control the time invariant feature of the inefficiency component. The results of this study show that trade policy on openness, machinery imports, stock of R&D, landlockedness, and quality of institutions play a significant and quantitatively important role in explaining these differences in efficiency scores in SSA; whilst human capital has an insignificant effect on inefficiency. We argue that SSA countries should gear their efforts in enhancing these efficiency boosting factors.

* Corresponding author. Tel.: +44 161 306 3666.
*E-mail addresses:* mdanquah@ug.edu.gh (M. Danquah), osman.ouattara-2@manchester.ac.uk (B. Ouattara).

[1] This divergence of SSA growth is well documented as the "African growth tragedy" (see Easterly and Levine, 1997).

[2] Along this same line, Devarajan et al. (2003) argue strongly that it is total factor productivity rather than the level of investment that has been the constraint to growth.

[3] Explained in the context of production possibilities frontier (PPF), efficiency change brings about a movement of a country towards or away from the PPF, whilst technical progress entails a shift of the PPF.

[4] This is a variant of the original Battese and Coelli (1995) model.

http://dx.doi.org/10.1016/j.econmod.2014.10.019
0264-9993/

The remainder of the paper is structured as follows. In Section 2 we discuss the methodology adopted in this paper. Section 3 provides a description of the data. The empirical evidence is presented in Section 4 whilst Section 5 focuses on the concluding remarks.

## 2. Methodology

We apply stochastic frontier analysis in a macroeconomics context, where countries are producers of output given inputs to empirically examine the determinants of technical efficiency in SSA. The stochastic frontier method constructs an efficient frontier by imposing a common production frontier technology across all countries in the sample. Deviations from the frontier are decomposed into inefficiency and noise. The introduction of the disturbance term to represent noise captures the effects of exogenous shocks beyond the control of the analysed unit, thereby reducing the volatility in the temporal patterns of efficiency measures. This closely matches the concept of frontier technology and the innovation of technology found in growth theory (Acemoglu et al., 2006; Aghion et al., 1998, 2002). In this context, countries can be thought of as operating either on or within the frontier, with the distance from the frontier reflecting inefficiency.[5]

To study the determinants of efficiency, two methodological approaches have been adopted in the SFA literature. The first approach, known as the two stage approach, consists of estimating efficiency scores in a first stage, and then in the second stage regress these scores against a set of explanatory variables. However, this approach suffers from a fundamental contradiction (see Kalirajan, 1981; Pitt and Lee, 1981). Indeed, the first stage assumes that inefficiencies are independent and identically distributed whilst the second stage contradicts the identical distribution assumption of the first stage (see Kumbhakar et al., 1991; Reifschnieder and Stevenson, 1991). The second approach is made up of models to overcome this problem by estimating both the frontier and efficiency effects in one stage. A popular version of this approach, the Battese and Coelli (1995) model for applications in panel data is preferred over the other frontier techniques in that it overcomes this contradiction and allows the simultaneous estimation of the parameters of the stochastic production frontier and the inefficiency effects model.[6] In this paper, we employ a variant of the Battese and Coelli (1995) model which allows the variance effects to be non-monotonic.

### 2.1. Production frontier

In order to simplify our analysis and remain consistent with the existing literature, we follow the models of economic growth in assuming that technology is global (see Howitt, 2000; Solow, 1956). The production frontier estimated using the SFA represents the maximum output that can be obtained from any given input vector, that is, the upper boundary of the production possibilities set. The input–output combination of each country is located on or below the production frontier.[7] We define the input vector as consisting of physical capital stock (K), labour force (L) and the stock of human capital (H). A time trend (T) common to all countries that capture technical progress over time is also included. Therefore, the stochastic frontier production function can be described as

$$Y_{it} = f(K_{it}, L_{it}, H_{it}, T; \beta) TE_{it} e^{v_{it}}. \tag{1}$$

The production technology in logarithms is set out in Eq. (2), where $y_{it}$ represents the maximal output in country $i$ at time $t$,

$$y_{it} = f(k_{it}, l_{it}, h_{it}, T; \beta) + \ln TE_{it} + \ln e^{v_{it}}. \tag{2}$$

Given that technical efficiency, $TE_{it} = e^{-u_{it}}$, Eq. (2) can be written as

$$y_{it} = f(k_{it}, l_{it}, h_{it}, T; \beta) + v_{it} - u_{it} \tag{3}$$

where $u_{it}(0 < u_{it} \le 1)$ measures technical inefficiency and $v_{it}$ captures the random character of the frontier caused by measurement error or other effects not captured by the model.

An important issue with regard to the estimation of Eq. (3) is the functional form of the production frontier. As a result of the questions raised over the suitability of the Cobb–Douglas functional form and the inclination for the translog stochastic frontier specification (see Duffy and Papageorgiou, 2000; Kneller and Stevens, 2003), we apply the translog specification (with non-neutral technology) in Eq. (4) to characterise the production frontier (see also Table 1 for a test of Cobb–Douglas against the translog):

$$\begin{aligned} y_{it} = {} & \beta_0 + \sum_{n=1}^{3} \beta_n \ln x_{nit} + \frac{1}{2} \sum_{n=1}^{3} \sum_{j=1}^{3} \beta_{nj} \ln x_{nit} \ln x_{jit} + \sum_{n=1}^{3} \beta_{tn} T \ln x_{nit} \\ & + \beta_t T + \frac{1}{2} \beta_{tt} T^2 + \sum_{r=1}^{3} \rho_r D_r + v_{it} - u_{it} \end{aligned} \tag{4}$$

where $y_{it}$ is log output of country $i$ in time $t$, $x_{nit}$ is the $n$th factor input used by the $i$th country in time $t$ to produce $y_{it}$. We include three inputs into the production process, specifically physical capital, labour and human capital respectively. Eq. (4) also includes regional dummies ($D_r$) for Latin America and the Caribbean (LAC), sub-Saharan Africa (SSA), Asia (ASIA) and OECD. These capture variances in the initial level of technology for these regions and are preferred to country-specific fixed effects (Temple, 1999). The variable $t$ is a proxy for technical progress and is explicitly intended to capture domestic technical progress. The $\beta$'s are parameters to be estimated. Finally, $u_{it}$, where $u_{it} \ge 0$ is the technical inefficiency error component and $v_{it}$ with $v_{it} \sim iid\ N(0, \sigma_v^2)$ being the random noise error component.

### 2.2. Inefficiency effects

Much of the empirical literature on efficiency using panel data models have examined intermediate cases, in which the inefficiency term is of a form more or less like

$$u_{it} = g(\mathbf{z}_{it})|Ui|, \tag{5}$$

where $Ui$ is half normal or truncated normal. In this case, inefficiency varies through time, but in a somewhat restricted fashion. Most current studies employing the SFA have used the Battese and Coelli monotonic 'decay' specification,

$$u_{it} = \exp[\eta(t-T)] \times |Ui|, \tag{6}$$

where $t$ is the period, and $T$ is the last period. The stochastic part is $Ui$ which is time invariant. Thus, in this form, there is a patterned variation through time, a simple exponential function determined by the parameter $\eta$.

However, Greene (2005, 2007) notes that, even with the time variation produced by $g(t)$, the assumption of time invariant $Ui$ can severely distort the estimated model and implied inefficiency estimates. Greene (2007) shows that results from the monotonic 'decay' specification are still vastly different from models in which the random part varies with time. These results therefore, suggest that the reality that the random component is still time invariant remains a substantive and detrimental restriction in the popular BC monotonic 'decay' specification. Hence, the

[5] Over time, a country can reduce its inefficiencies and reach the frontier or the frontier itself can shift outwards over time, indicating technical progress.

[6] Kumbhakar et al. (1991), Reifschnieder and Stevenson (1991) and Huang and Liu (1994) are some of the earlier studies that presented models to overcome this problem by estimating both the frontier and efficiency effects in one stage.

[7] In order to account for the possible complementarity between human capital and physical capital, human capital is included as a separate term in the production function (see Griliches, 1969; Mankiw et al., 1992; Kneller and Stevens, 2006).