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COMPARISON OF STOCHASTIC FRONTIER APPROACHES FOR ESTIMATING NATIONAL EFFICIENCY: AN APPLICATION TO SUB-SAHARAN AFRICAN COUNTRIES

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In this paper, we attempt to estimate pure national (technical) efficiency for 19 SSA countries over the 1960-2010 periods. In doing this, we compare conventional stochastic frontier models for panel data with a number of recently developed models which seek to control for unobserved heterogeneity in the inefficiency component. We find that the 'true' random effects model that treats unobserved heterogeneity in our national dataset generates more reasonable efficiency estimates. Moreover the results confirm that most SSA countries operate far from the efficient frontier.

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JEL Classification: D24, 047, 055

1. INTRODUCTION

"The errors which arise from the absence of facts are far more numerous and more durable than those which result from unsound reasoning respecting true data."
Charles Babbage (2002)

Recent empirical literature on economic growth investigating the proximate causes of the enormous differences in per capita income across countries usually indicate that these differences in incomes are largely a consequence of differences in total factor productivity (TFP) growth (see Krugman, 1994; Prescott, 1998; Hall and Jones, 1999; Easterly and Levine, 2001). A large body of studies aimed at investigating why sub Saharan Africa (SSA) has been growing so slowly also broadly agree that low total factor productivity growth is the main impediment to the growth performance in SSA countries (Aryeetey and Fosu, 2002; Collins and Bosworth, 2003; Ndulu and O'Connell, 2000, 2003, 2007; Berthelemy and Söderling, 2002; Hoeffler, 2002; Tahari et al., 2004;

Danquah and Ouattara, 2015, 2016). Using the Collins and Bosworth growth accounting-based decomposition of sources of growth, Aryeetey and Fosu (2002) found that TFP's contribution to economic growth was negative at -0.42% for SSA and -1.15% for Ghana over the 1960-1997 period. Aryeetey and Fosu (2002) concludes that, overall, the slow rate of per capita income growth in Ghana over 1960-1997 seems to be largely attributed to productivity rather than to production inputs. Revised Collins and Bosworth growth accounting decompositions by O'Connell and Ndulu (2003) for 19 SSA countries over the 1960-2000 period also show that, the overall contribution of TFP to growth was negative at -0.09%. Similarly, 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 in SSA. Current quantifiable progress reports of the Millennium Development Goals (MDGs) and Poverty Reduction Strategy Papers (PRSPs) of most sub-Saharan African countries indicate that a significant boost in TFP growth is required in order to double the average annual growth rate to achieve the targets set out in these programs.

The importance of TFP growth across countries has pushed forward the debate on the determining factors of productivity, particularly technical efficiency of countries on the research agenda.[1] Countries that are technically inefficient operates far from the best efficient frontier and have a lower ability to absorb new technology, thereby producing less output than the ones operating with the best available technical knowhow, ceteris paribus. This deficiency, which is evident in the distance of the country from the production frontier, is known as technical inefficiency (Farrell, 1957). Prescott (1998) for instance, attributes the key to understanding the evolution of the world income distribution to cross country differences in the level of technical efficiency. His findings are supported by Jerzmanowski (2007), who points out that inefficiency appears to be the main explanation for the low incomes throughout the world, explaining 43 percent of variation in incomes. For countries in SSA, improvements in national efficiency become even more of an imperative for growth and development. As a result, the accuracy of technical efficiency measures is important in policy discussions. It is therefore important to define and measure efficiency in ways that respect economic theory and at the same time provide useful information to managers of the economy.

Estimating technical inefficiency within the stochastic frontier framework (i.e. based on the notion of best practice frontier) is particularly common in the applied economic literature.[2] An extensive review of the body of techniques is given in Sena (2003),

[1] Economic efficiency has technical and allocative components. The technical component refers to the ability to elude waste, either by producing as much output as technology and input usage allow or by utilising as little input as required by technology and output production

[2] The reasons for these are twofold. First, the stochastic frontier method has deep roots in the economic theory. In this case, efficiency is measured as the distance from a best practice frontier (or the boundary of the production possibility frontier), computed in accordance with the axioms of the production theory. Second, the concept of a distance from the standard allows us to operationalise the concept of inefficiency, providing ready to use information for policy makers.

Murillo-Zamorano (2004) and Fried et al. (2008). Generally, studies on national efficiency of countries have employed the conventional stochastic frontier approaches, while the focus of these studies has been on factors explaining national efficiency. These empirical applications in the literature utilising the stochastic frontier approaches to study technical efficiency across countries do not establish the 'accurateness' of national efficiency estimates. Particularly, studies employing the stochastic frontier approach have either used the pooled data model or the Battese and Coelli (1992, 1995) specification, while many of them have rather focused on the covariates of inefficiency and not efficiency estimates (see Henry et al., 2008; Iyer et al., 2008; Mastromarco and Ghosh, 2009; Danquah et al., 2018). Greene (2005, 2007) points out that the inefficiency estimates from the conventional stochastic frontier approaches particularly the BC model does relax the time invariance assumption but it appears that the fact that the random component is still time invariant can be a detrimental and substantive restriction on the inefficiency estimates. Moreover, the tricky modelling issue of separating unobserved heterogeneity from estimated inefficiency are not addressed by conventional stochastic frontier approaches. For example, in national datasets, not all the relevant data are always available while some factors are difficult to quantify and rarely considered when empirical inefficiency comparisons are made. Given that such input differences are exogenously determined, the conventional stochastic frontier approaches will provide a biased measure of national efficiency.

This paper contributes to the literature on growth and productivity on two main fronts. First, to improve on the existing studies we employ recently developed panel data modelling techniques that treat time invariant effects and separate unobserved heterogeneity from inefficiency term (i.e. control for unobserved heterogeneity).This allows us to obtain an inefficiency measure that captures pure technical inefficiency. Although these modelling approaches have been widely applied in some areas of research such as health and agricultural sectors among others (see Greene, 2004; Filippini et al., 2008; and Carroll et al., 2011, among others) their use in the macroeconomic context has been virtually inexistent. Indeed, we adopt the new class of stochastic frontier models (i.e. time varying 'true' fixed and 'true' random effects models) that treats unobserved heterogeneity in our panel data framework and the conventional models (pool, fixed, random and Battese and Coelli time decay models). The second contribution of the study is the focus on SSA due the lack of studies in this region, despite the importance of national efficiency measures for policy discussions on productivity and economic growth. Increased productivity would lead to more and more sustained outputs to provide the resources for individual and national level actions to reduce or end poverty. The sample consists of 19 countries over the 1960-2010 period. The paper, therefore has two key objectives. The first objective is to compare the various modelling approaches and identify the most robust and reliable technique to derive pure technical efficiency. The second objective is to investigate the extent to which SSA countries are close to the global efficiency frontier. The main findings of this paper can be summarised as follows. Among the class of estimators used in this study to derive pure national technical efficiency, we find that the 'true' random effect model that treats unobserved heterogeneity in our dataset provides more reliable estimates of efficiency. As expected, the paper also finds that SSA countries operate far from the efficiency frontier.

The rest of the paper is organised as follows. In the next section, we introduce the frontier methodology and data employed for the analysis of national efficiency. The empirical results and analysis of technical inefficiency estimates are presented in sections 3. The last section concludes.

2 METHODOLOGY AND DATA

Remaining consistent with the existing literature and the early models of economic growth, we assume that technology is global (Solow, 1956; Howitt, 2000) and that output in country i at time t is given by

$$Y_{it} = f(K_{it}, L_{it}, H_{it}), \tag{1}$$

where Y_{it} is output (GDP) of country i at time t, $f(\cdot)$ is suitable functional form, K_{it}, L_{it}, and H_{it} are defined as the stock of physical capital, labour force and stock of human capital for country i at time t respectively.[3] Following Griliches (1969) and Mankiw et al. (1992), this study includes human capital stock as a separate term in the production function in order to account for the possible complementarity between human capital and physical capital stock. The estimation procedure for the stochastic frontier approach (SFA) is discussed in the subsequent sections.

2.1. SFA Approach: Specification and Estimation of the Stochastic Frontier Models

We assume that some countries may lack the ability to employ existing technologies as efficiently as possible and consequently produce less than the optimal output. Therefore the actual observable output produced in each country i at time $t(Y_{it})$ is then better described by the following stochastic frontier production function;

$$Y_{it} = f(K_{it}, L_{it}, H_{it}, T; \beta) TE_{it} e^{v_{it}}, \tag{2}$$

where T is a time trend common to all countries and is intended to capture technical progress over time and β is an unknown parameter to be estimated. TE_{it} represent technical efficiency and is defined as the exponential of -u_{it}, where $u_{it} > 0$ and is a measure of the shortfall of output from the frontier (technical inefficiency) for each

[3] In this study, we also experiment without human capital but the results do not change significantly.

country in the sample. v_{it} embodies measurement errors, any statistical noise and random variations of the frontier across countries.

The production model in logarithms will be of the form

$$lnY_{it} = lnf(K_{it}, L_{it}, H_{it}, T; \beta) + ln(TE_{it}) + ln(e^{v_{it}}). \tag{3}$$

Replacing TE_{it} with $exp(-u_{it})$, equation (3) can be reformulated as

$$lnY_{it} = lnf(K_{it}, L_{it}, H_{it}, T; \beta) + v_{it} - u_{it}, \tag{4}$$

where $u_{it} > 0$, but v_{it} may take any value and is assumed to be half-normally distributed.

An important issue with regard to the estimation of equation (4) 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 and Kumbhakar and Wang, 2005), we apply the translog specification (with non-neutral technology) in equation (4) to characterise the production frontier (see also Table 2 for test of Cobb-Douglas against the translog):

$$y_{it} = \beta_0 + \sum_{n=1}^{3} \beta_n lnx_{nit} + \frac{1}{2}\sum_{n=1}^{3} \sum_{j=1}^{3} \beta_{nj} lnx_{nit} lnx_{jit} + \sum_{n=1}^{3} \beta_{tn} T lnx_{nit} + \beta_t T + \frac{1}{2}\beta_{tt} T^2 + \sum_{r=1}^{3} \rho_r D_r + v_{it} - u_{it}, \tag{5}$$

where y_{it} represents the logarithm of Y_{it} and xn_{it} denotes an n-th input variable, T is a time trend representing technical change and β are unknown parameters to be estimated. The time trend T, interacts with the input variables, and thus allows for non neutral technical change. Although the study focuses on SSA, countries from other regions are included in order to be able to estimate the best practice frontier. As a result, regional dummies (D_r) for Latin America and the Caribbean (LAC), sub Saharan Africa (SSA), Asia (ASIA) and OECD are included. For convenience, the translog production frontier function in equation (5) can be written as;

$$y_{it} = \alpha + \beta' x_{it} + v_{it} - u_{it}, \tag{6}$$

where the proxy for technical change T is included in $\beta' x_{it}$.

The stochastic frontier production model in equation (6) is estimated using six different stochastic frontier methods. The differences between the various specifications are related to the assumptions and behaviour imposed on the error term, $\varepsilon_{it} = v_{it} - u_{it}$, specifically the inefficiency component, u_{it} and country specific effects. Table 1 provides a summary for the model specifications of country specific components, the random error, inefficiency as well as the relative efficiency for all stochastic frontier models used for the estimation of efficiency in the study.

Model I is a base case pooled frontier model (Aigner et al., 1977) estimated by maximum likelihood (ML) method. In estimating model I, the following distributional assumptions are made: v_{it}: i.i.d. $N(0,\sigma_v^2)$, u_i: i.i.d. $N^+(0,\sigma_u^2)$ and v_{it} and u_{it} are distributed independently of each other and of the regressors.

Table 1. Econometric Specification of Stochastic Frontier Models

Model	Country-specific component	Random error ε_{it}	Inefficiency u_{it}	Relative Efficiency
Model I	None	$\varepsilon_{it} = v_{it} - u_{it}$ v_{it}: i.i.d. $N(0,\sigma_v^2)$ u_{it}: i.i.d. $N^+(0,\sigma_u^2)$	$E(U_{it}\|\varepsilon_{it})$	$E(\exp(-u_{it}\|\varepsilon_{it}))$
Model II	u_i: i.i.d. $N^+(0,\sigma_u^2)$	$\varepsilon_{it} = v_{it} - u_i$ v_{it}: i.i.d. $N(0,\sigma_v^2)$ u_i: i.i.d. $N^+(0,\sigma_u^2)$	$E(U_i\|\varepsilon_i)$	$E(\exp(-u_i\|\varepsilon_i))$
Model III	Fixed	$\varepsilon_{it} = v_{it}$	$u_i = \max(\alpha_i) - \alpha_i$	$u_i = \max((\alpha_i) - \alpha_i)$
Model IV	u_i: i.i.d. $N^+(0,\sigma_u^2)$	$\varepsilon_{it} = v_{it} - u_i$ $u_{it} = u_i \times \exp[-\eta(t-T)]$ v_{it}: i.i.d. $N(0,\sigma_v^2)$ u_i: i.i.d. $N^+(0,\sigma_u^2)$	$E(u_{it}\|\varepsilon_{it})$	$E(\exp(-u_{it}\|\varepsilon_{it}))$
Model V	Fixed (group dummies α_i)	$\varepsilon_{it} = v_{it} - u_{it}$ v_{it}: i.i.d. $N(0,\sigma_v^2)$ u_{it}: i.i.d. $N^+(0,\sigma_u^2)$	$E(u_{it}\|\varepsilon_{it})$	$E(\exp(-u_{it}\|\varepsilon_{it}))$
Model VI	ω_i: i.i.d. $N(0,\sigma_\omega^2)$	$\varepsilon_{it} = v_{it} - u_{it}$ v_{it}: i.i.d. $N(0,\sigma_v^2)$ u_{it}: i.i.d. $N^+(0,\sigma_u^2)$	$E(u_{it}\|\varepsilon_{it})$ $w_{it} = \omega_i + \varepsilon_{it}$	$E(\exp(-u_{it}\|\varepsilon_{it}))$

Model I does not assume any country-specific effects and also does not have the ability to distinguish between inefficiency and unobserved heterogeneity of the countries understudy. Models II to VI are panel data estimators of the stochastic frontier model. The random effects (RE) model,

$$y_{it} = \alpha + \beta' x_{it} + v_{it} - i_i, \tag{7}$$

proposed by Pitt and Lee (1981), is presented in Model II. Although Model II is a panel estimator, $-u_i$ is time invariant. Model II is estimated by maximum likelihood. The linear fixed effects (FE) model proposed by Schmidt and Sickles (1984) is also presented in Model III as

$$y_{it} = \alpha_i + \beta' x_{it} + v_{it}. \tag{8}$$

The main weakness of Model II and Model III are that they force any time-invariant country-specific heterogeneity into the same term that is being used to capture the inefficiency (Greene, 2004, 2005, 2007). Consequently, these models do not have the ability to distinguish between time-invariant unobserved heterogeneity and technical inefficiency. Any time invariant country level-specific effects are treated as inefficiency.

Model IV is the simple Battese and Coelli (1995) time decay model which is an extension to the RE framework and is specified as

$$y_{it} = \beta' x_{it} + v_{it} - u_{it}, \tag{9}$$

where $u_{it} = g(z_{it})|U_i|$ and U_i is half normal. We note that, in the Battese and Coelli alternative, the time variation of inefficiency terms is not stochastic and is assumed to follow a more or less restrictive form (Greene, 2005, 2007). The drawback of this model is that any time invariant unobserved heterogeneity may also be pushed into the inefficiency component.

In models V and VI, we introduce the alternative 'true' fixed-effects and 'true' random-effects models proposed by Greene (2004, 2005) to deal with the unobserved heterogeneity, i.e. disentangling unobserved heterogeneity and inefficiency.

The 'true' fixed effects (TFE) is specified as

$$y_{it} = \alpha_i + \beta' x_{it} + v_{it} - u_{it}, \tag{10}$$

and estimated by 'brute force' maximum likelihood, (by simply creating dummy variables for each country). TFE model treats country-specific time-invariant fixed effects (α_i) and time-varying inefficiency (u_{it}) separately and is therefore able to distinguish between the unobserved heterogeneity and inefficiency. In this way it tries to overcome some limitations of the conventional linear fixed effects model. The shortcoming of the TFE model is the incidental parameters problem.

The 'true' random-effects (TRE) model is specified as

$$y_{it} = \alpha + \beta' x_{it} + \omega_i + v_{it} - u_{it}. \tag{11}$$

In the TRE, ω_i (which is assumed to have an i.i.d. normal distribution) is a time-invariant and country-specific random term meant to capture unobserved heterogeneity or country specific heterogeneity. As proposed by Greene we estimate the 'true' random effects model by Maximum Simulated Likelihood (MSL) by integrating out ω_i using Monte Carlo method.

The fact that the TFE and TRE accommodate the possibility of time invariant heterogeneity, to the extent possible, is preferable to ignoring it altogether, as in the conventional RE and FE panel models (Greene, 2004). It is however expected that findings from any of the above stochastic frontier specifications which is considered as the preferred model must in some way be consistent with economic intuition.

2.2. Data

The dataset used in this study is a panel of 80 countries (including the 19 SSA countries)[4] for the period 1960–2010. The dataset is expanded to include other countries in Latin America and the Caribbean (LAC), Asia and OECD in order to enable us determine the globally efficient frontier (see Appendix A, Table A1 for list of countries). The output variable is captured by the log of real GDP while the inputs are log values of the physical capital stock, labour force and stock of human capital. The real Gross Domestic Product data are derived from the World Development Indicators-WDI (2012). In line with the existing literature (see Collins and Bosworth, 2003; Ndulu and O'Connell, 2003), the total labour force is measured by the economic active population, that is, the population aged between 15 and 64 years and also sourced from the WDI (2012). We follow the methodology by Nehru and Dhareshwar (1993) for our dataset on physical capital stock. Using the perpetual inventory method with a revised depreciation rate of 0.05 percent we extend the dataset to 2010.[5] For the human capital (H) variable, we use the total human capital obtained from Barro and Lee (2010).This new dataset exploits new sources of information and introduces different corrections to improve the signal-to-noise ratio in the schooling series. The human capital estimates of Barro and Lee (2010) are measured by the mean years of schooling in the population aged 15 years and over. Table A2 in the appendix presents summary statistics of the variables.

3 EMPIRICAL RESULTS

3.1. Stochastic Frontier Models: Results and Analysis

We perform various tests on selection of the functional form, the validity of the coefficients of the translog form and non neutral technological hypothesis (see Table 2). First of all we applied the generalised likelihood ratio test to decide between the null hypotheses of Cobb–Douglas functional form versus the alternative of the translog specification. The null hypothesis of Cobb–Douglas functional form is rejected. The null hypothesis that the coefficients of the translog form equal zero is also rejected at the five percent significance level. The last test which consists of testing the null hypothesis that there is no technological change over time is also rejected at the ten percent significance level.[6]

Table 3 presents estimated production frontier functions based on the SFA specifications in Table 1. Estimated technical inefficiencies and efficiencies are computed using the methods discussed earlier. The overall level of inefficiency and efficiency in the sample is suggested by the values at the bottom of Table 3. To simplify our analysis and comparisons between the different stochastic frontier estimators, we use

[4] We limit the sample to 19 SSA countries due to data availability.

[5] We obtain the dataset on physical capital stock and Collins and Bosworth measure of human capital index from Susan Collins. We are grateful to Susan Collins for access to the data.

[6] All results are obtained using LIMDEP 9.0.

the direct estimate of inefficiency $\hat{u}_{it}$.

Table 2. Generalised Likelihood-ratio Test of Null Hypothesis for Parameters in the Stochastic Frontier Production Function

Null hypothesis	Log likelihood	Likelihood Ratio test Statistics	Critical value (α=0.05)	Decision
Preferred model: Translog	-846.861			
A Cobb-Douglas function is adequate	-851.421	246.026	12.591	Reject Ho
Technical change is Hicks–neutral	-1170.933	158.826	12.591	Reject Ho
No technical change	-989.3157	278.567	9.487	Reject Ho
Br./Pagan LM Chi-sq[3]		136.30 (.000)a		

The critical values are at 5% level of significance and are obtained from Table 1 of Kodde and Palm (1986). a Probability in parenthesis.

The estimates of λ, σ, σu and σv (see Table 3) are reasonable, as are the remaining parameters and the estimated inefficiencies. The estimate of λ is statistically significant suggesting that there is evidence of technical inefficiency in the dataset. These estimates are smaller and similar to the time varying TFE and TRE models. The estimates of $\lambda = \sigma u/\sigma v$ for the time invariant models (II and III), are comparatively larger than the time varying models (IV, V and VI). The variance decomposition is dominated by $u(\sigma u)$. The time invariant Pitt and Lee model has the highest σu of 0.605 while σv is fairly even for all specifications with the exception of the TRE, which is rather very small. σw which is supposed to treat all time invariant effects and peculiar to the TRE model is significant and indicate that the time varying TRE model is moving some of the variation out of u_i. This would be consistent with purging the time invariant u_i of sometime invariant heterogeneity.

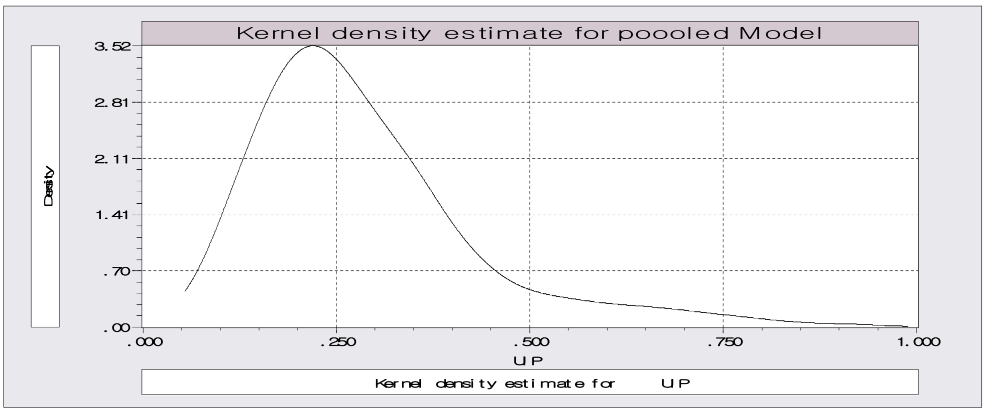

Figure 1. Estimated Kernel Density for Pooled Stochastic Frontier Model

Table 3. Estimated Stochastic Frontier Models

Parameters	PSF	RE	FE	B&C	TFE	TRE
CONSTANT	-0.098	0.857***	-	1.143***	-	0.381***
	(0.123)	(0.085)		(0.056)		(0.045)
K	0.944 ***	0.948***	0.949	0.946***	0.939***	0.937***
	(0.013)	(0.005)	(0.008)	(0.004)	(0.018)	(0.003)
L	0.155***	0.065***	0.056	0.073***	0.170***	0.092***
	(0.021)	(0.017)	(0.018)	(0.010)	(0.017)	(0.008)
H	0.228	0.106	0.954*	0.119	0.242*	0.141**
	(0.289)	(0.242)	(0.494)	(0.148)	(0.128)	(0.065)
TIME	0.004	-0.006**	-0.007	-0.023***	0.008**	-0.009**
	(0.004)	(0.002)	(0.002)	(0.002)	(0.003)	*(0.002)
K×K	0.002**	0.007***	0.007	0.008***	0.002**	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
L×L	-0.041***	-0.032***	-0.032	-0.013***	-0.043***	-0.026***
	(0.003)	(0.003)	(0.004)	(0.002)	(0.002)	(0.001)
H×H	0.522**	-0.352**	-0.684	0.021	0.551***	0.439***
	(0.237)	(0.170)	(0.405)	(0.104)	(0.152)	(0.071)
Time×Time	0.001**	0.000	0.000	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
K×L	0.017***	0.017***	0.017	-0.001	0.0161***	0.016***
	(0.002)	(0.001)	(0.003)	(0.001)	(0.001)	(0.001)
K×H	-0.292***	-0.378***	-0.369	-0.112***	-0.274***	-0.315***
	(0.028)	(0.017)	(0.036)	(0.014)	(0.020)	(0.011)
K×Time	0.002***	0.002***	0.002	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
L×H	0.358***	0.295***	0.295	0.156***	0.368***	0.234***
	(0.026)	(0.020)	(0.031)	(0.015)	(0.019)	(0.011)
L×Time	-0.002	-0.001***	-0.001	0.000	0.000	-0.001***
	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)
H×Time	-0.036***	-0.008**	-0.007	-0.031***	-0.041***	-0.022***
	(0.007)	(0.003)	(0.004)	(0.004)	(0.005)	(0.002)
λ	1.356***	3.003 ***	-	1.817***	1.460***	1.270***
	(0.063)	(1.016)		(0.102)	(0.075)	(0.263)
σ	0.445***	0.637	-	0.379	0.594***	0.342***
	(0.000)				(0.008)	(0.002)
σu	0.357	0.605***	-	0.332***	0.491	0.338
		(0.117)		(0.011)		
σv	0.263	0.201	-	0.183	0.336	0.054
σw	-	-	-	-	-	0.326***
						(0.003)
Estimated Inefficiencies, $\hat{u}_{it}$						
Mean	0.284	0.534	0.526	0.568	0.338	0.262
SD	0.143	0.281	0.272	0.362	0.089	0.203
Min	0.081	0.018	0.000	0.009	0.142	0.011
Max	0.961	1.450	1.504	2.425	0.942	1.065

Note: ***, ** and * denotes significance at 1%, 5% and 10% respectively. Parameters of regional dummies are omitted from Tables 3 for the sake of brevity. All model estimates are obtained by using Limdep. Estimated standard errors in parenthesis

Table 4. Correlation between Inefficiencies

	Pooled ML	Battese and Coelli	Random effects	Fixed effects	'True' random effects	'True' fixed effects
(a) Correlation coefficient						
Pooled ML	1.000					
Battese and Coelli	0.717	1.000				
Random effects	0.764	0.755	1.000			
Fixed effects	0.533	0.524	0.890	1.000		
'True' random effects	0.568	0.172	0.012	0.051	1.000	
'True' fixed effects	0.592	0.186	0.003	0.057	0.925	1.000
(b) Spearman rank correlation coefficient						
Pooled ML	1.000					
Battese and Coelli	0.653	1.000				
Random effects	0.769	0.753	1.000			
Fixed effects	0.429	0.400	0.634	1.000		
'True' random effects	0.525	0.083	0.007	0.059	1.000	
'True' fixed effects	0.571	0.102	0.005	0.055	0.922	1.000

The mean inefficiency estimate for the full sample of our pooled model (that ignores any commonalities or panel data effects) is roughly 28% with a standard deviation of 0.1431. The distribution of u_{it} is shown below (Figure 1).

The mean inefficiencies for the panel data models II-VI clearly show that the time varying 'true' fixed and random effects models represent a lower band of inefficiency estimates, 34% and 26% with a corresponding lower standard deviation of 0.0892 and 0.204 respectively. These estimates are similar to the pooled data set. On the other hand, the time invariant models in addition to the Battese and Coelli model have high average inefficiency estimates and standard deviations.

The simple and spearman rank correlation of the specifications (see Tables 4a and 4b), indicate that the apparent dissimilarity (shown by the means) between the pooled model, the time invariant and the Battese and Coelli models is superficial and may be misleading. The simple correlations between these models rather indicate a very strong similarity between them (see Table 4a).The perceptible disparity between the 'true' fixed and random effects models and the time invariant, as well as the Battese and Coelli models is however robustly confirmed. The simple and rank correlation between the random and the true random effects models is 1.1% and 0.6% respectively.

The scatter plots in figure 2a-2e indicate this strong correlation between the two time varying models, V and VI (Figure 2a) and the two time invariant models, II and III (Figure 2b). The Battese and Coelli model (IV) also have a strong correlation with the time invariant models. There is nearly no correlation between the time varying models and the time invariant models as well as the time varying models and Battese and Coelli model (Figures 2c, 2d and 2e).

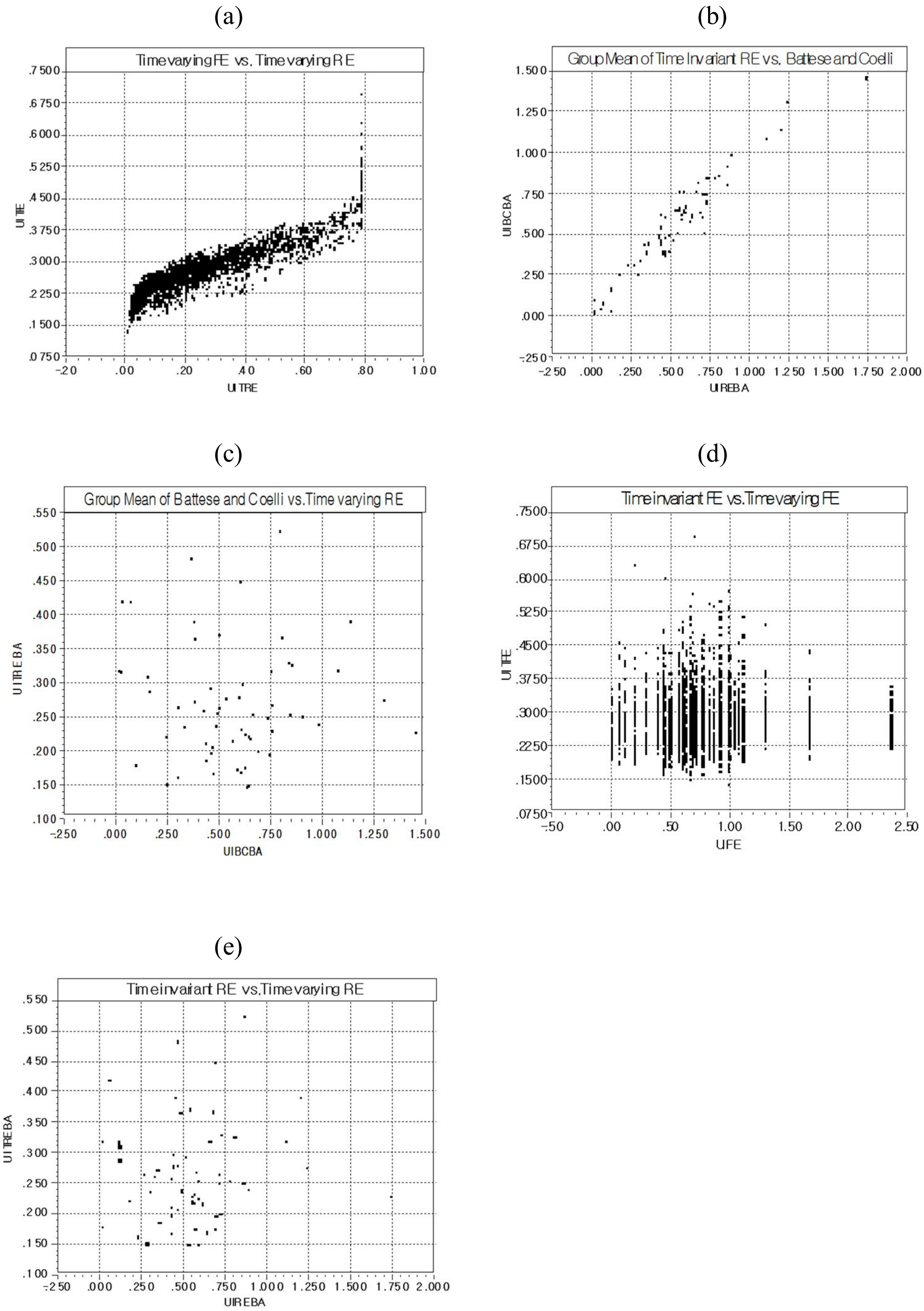

Figure 2. Scatter Plots based on Estimated Inefficiencies of Stochastic Frontier Models

In line with the robust estimation of technical efficiencies, we further analyse the mean and variation of the distributions for estimated inefficiencies of the different specification. The kernel density estimators show that the mean of the distribution for the TRE model is the lowest compared to the other models, while its variance is also considerably lower. In effect, the kernel density estimators for the two modelling platforms indicate that the mean and variance of the distribution of u_{it} for the time varying models is much lower and tighter while that of the time invariant model(u_i) and the Battese and Coelli model are dispersed (see Figure 3). Therefore, it is not only the means of the estimated inefficiencies that are much lower in the time varying models, but the full distribution over countries seems to have changed as well.

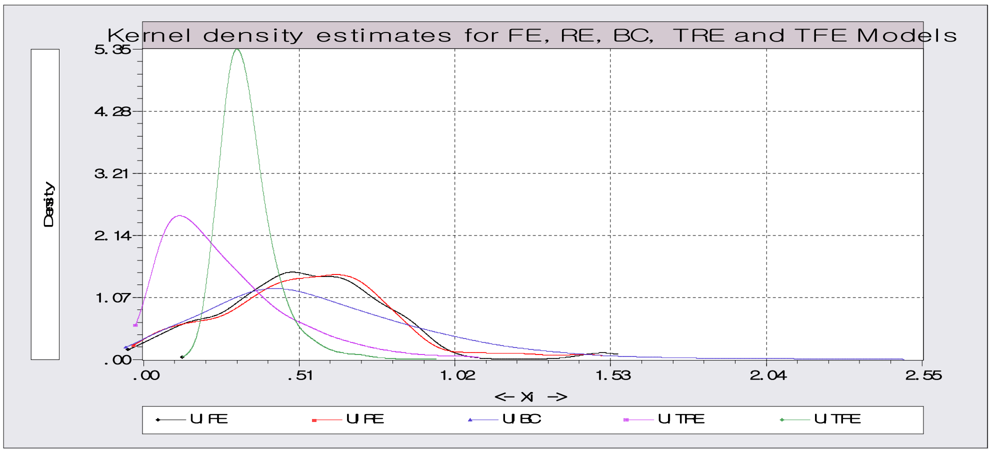

Figure 3. Kernel Density Estimates for BC, RE, FE, TRE and TFE Models

The higher inefficiency estimates and dispersed behavior of inefficiency in our time invariant models are not surprising. This confirms that the time invariant models' implicit assumption that inefficiency is the same in every period is particularly strong and unsuitable for our study. More importantly, we surmise that these models are carrying both the inefficiency and in addition any time invariant country specific heterogeneity. In the Battese and Coelli model which closely resembles the time invariant models, it appears that the fact that the random component is still time invariant remains a substantive and detrimental restriction to our specification. We note that the time varying model differs considerably from both time invariant models and the Battese and Coelli model.

The 'true' random effects model appears to be the best model specification for our study. It consistently treats unobserved heterogeneity in our panel data set as well as time invariant heterogeneity. The 'true' fixed effects model at a point appears to be over specified and saturated, unable to handle the heterogeneity in our panel data set.

Although it shows in the above analysis that the pooled model is comparatively inconsistent, nevertheless, we test for the evidence that the panel treatment using the 'true' random effects model is superior to the pooled model. The chi-square for the true random effects model is 868.32, which is quite high and therefore providing some basis for rejecting the hypothesis of the pooled model. As a final indication, we use the Breusch and Pagan (1980) Lagrange Multiplier statistics from our simple linear model (see Table 2). The value is 136.30. As a chi-square with three degrees of freedom, this support our conclusion that the time varying 'true' random effects model appear to capture pure technical inefficiency across SSA countries over the period.

3.1.1. Technical Efficiency Estimates for SSA

We estimate technical efficiency, $exp(-u_{it})$ for all the frontier models. Generally, there is a regional variation in the efficiency estimates. We observe that countries in the OECD and East Asia are most efficient with an overall average national efficiency greater than 94% in the 'true' random effects specification. Also some countries in Latin America, for instance, Mexico, Brazil and others like Israel were also efficient (see Table A3 in the appendix). The descriptive statistics of efficiency estimates for Sub-Saharan Africa is presented in Table 5. Recalling that the TRE model is the preferred specification of the stochastic production frontier model for our panel data, we can conclude that the overall average national efficiency for Sub-Saharan Africa from 1960 to 2010 is 78.3%. The overall median for the entire sample is 81.22%, whilst that for SSA is 80.0%. Comparing the median of efficiency estimates for SSA countries with the overall median for the sample (as is done in the frontier literature, see Mastromarco, 2002 among others) the median for SSA countries is below the overall median. This indicates that, overall SSA countries are relatively not efficient.

Table 5. Technical Efficiency Estimates for Sub-Saharan Africa, 1960-2010

Model	Mean	Median	Standard Deviation	Min	Max
Pooled ML	0.759	0.771	0.098	0.382	0.921
Random Effects	0.608	0.555	0.164	0.234	0.982
Fixed Effects	0.611	0.604	0.157	0.222	1.000
Battese and Coelli	0.600	0.578	0.188	0.088	0.991
'True' Fixed	0.715	0.724	0.059	0.390	0.866
'True' Random	0.783	0.798	0.141	0.344	0.989

Note: All model estimates of efficiency are obtained by using Limdep 9

Table 6. Mean Efficiency Levels and Rank of Countries, 1960-2010

	Pooled ML		Random Effects Pitt and Lee		Battese and Coelli		'True' Fixed		'True' random	
	Country	Mean Efficiency	Country	Mean Efficiency	Country	Mean Efficiency	Country	Mean Efficiency	Country	Mean Efficiency
1	Rwanda	0.881	Rwanda	0.981	Rwanda	0.982	Madagascar	0.722	South Africa	0.851
2	Sierra Leone	0.875	Sierra Leone	0.938	Ethiopia	0.880	South Africa	0.722	Mauritius	0.839
3	Ethiopia	0.872	Ethiopia	0.931	Sierra Leone	0.854	Ghana	0.721	Kenya	0.837
4	Uganda	0.846	Uganda	0.788	Uganda	0.825	Tanzania	0.721	Ghana	0.833
5	Madagascar	0.831	Cameroon	0.745	Cameroon	0.739	Mauritius	0.721	Tanzania	0.824
6	Cameroon	0.829	Madagascar	0.741	Madagascar	0.721	Mozambique	0.719	Senegal	0.801
7	Tanzania	0.807	Cote D'Ivoire	0.635	Cote D'Ivoire	0.614	Zambia	0.719	Mali	0.797
8	Senegal	0.791	Senegal	0.629	South Africa	0.599	Cameroon	0.718	Cote D'Ivoire	0.791
9	Cote D'Ivoire	0.788	Tanzania	0.589	Senegal	0.588	Cote D'Ivoire	0.717	Madagascar	0.791
10	Ghana	0.762	South Africa	0.555	Ghana	0.569	Mali	0.717	Ethiopia	0.789
11	South Africa	0.762	Ghana	0.553	Tanzania	0.546	Sierra Leone	0.717	Cameroon	0.789
12	Mozambique	0.724	Mozambique	0.498	Nigeria	0.532	Senegal	0.714	Zambia	0.773
13	Zimbabwe	0.698	Zimbabwe	0.485	Mozambique	0.531	Uganda	0.711	Mozambique	0.754
14	Kenya	0.689	Kenya	0.482	Malawi	0.462	Kenya	0.708	Sierra Leone	0.743
15	Mauritius	0.679	Mauritius	0.439	Kenya	0.461	Rwanda	0.706	Rwanda	0.726
16	Mali	0.671	Nigeria	0.439	Zimbabwe	0.455	Ethiopia	0.704	Zimbabwe	0.721
17	Nigeria	0.668	Mali	0.426	Mali	0.437	Malawi	0.703	Uganda	0.718
18	Malawi	0.653	Malawi	0.412	Mauritius	0.382	Zimbabwe	0.703	Nigeria	0.662
19	Zambia	0.533	Zambia	0.289	Zambia	0.295	Nigeria	0.701	Malawi	0.633

We also present the mean and median efficiency levels as well as the rank of SSA countries in Tables 6 and 7 based on the models specifications. This is done in order to allow us to reconcile the various specifications with economic intuition.7 The rank and median efficiency estimates of countries in the pooled, random effects and Battese and Coelli models are not surprising. It shows that countries like Rwanda, Sierra Leone, Ethiopia and Uganda are the most efficient, thereby producing mixed economic intuition. We surmise that, the failure of the pooled, Battese and Coelli and the Pitt and Lee random effects models to treat unobserved heterogeneity as well as the strong time invariant assumptions in the latter make these models unsuitable for the study. On the other hand, the rank and median efficiency estimates of countries in 'true' random effects model shows a rank order and estimates which seem very intuitive with countries like South Africa and Mauritius being efficient.

As observed in Table 6, these countries that appear to be most efficient in the misspecified models appear in the lower ranks in the 'true' random effects model. This in a way supports our earlier observations that the 'true' random effect model somehow accommodates the time varying features and the time invariant unobserved heterogeneity in our panel dataset. We suggest that a model that provides scope for unmeasured heterogeneity, such as the 'true' random effects model (in our case) is likely to yield an inefficiency measure that attempts to capture pure technical inefficiency to the one that does not.

The higher levels of national efficiency in the OECD and East Asia reflect the higher and immense contributions of TFP growth to the strong economic performance of the countries in these regions. In contrast, the SSA region which has lower levels of efficiency in our study, indicate the abysmal contributions of TFP growth to growth and development (see O'Connell and Ndulu, 2003). The findings therefore support earlier studies on national efficiency and the evolution of world incomes, that is, countries that are efficient have higher TFP growth which contributes immensely to a strong economic performance and higher incomes (see Prescott, 1998 and Jerzmanowski, 2007).

4 CONCLUSIONS

This paper uses different specifications of the stochastic frontier model to determine an inefficiency measure that seeks to capture pure technical inefficiency across countries in SSA.

With regards to the different specifications in the stochastic frontier models, the time varying 'true' random effect specification estimated by maximum simulated likelihood (MSL) is preferred to the pooled, simple time decay Battese and Coelli and the time invariant fixed and random effects models. It appears that the failure of the pooled,

[7] Henry et al. (2008) using the Battese and Coelli method report an average efficiency score (similar to our Battese and Coelli estimates) of 60% for Sub- Saharan Africa.

Battese and Coelli and the Pitt and Lee random effects models to treat unobserved heterogeneity as well as the strong time invariant assumptions in the latter make these models unsuitable for the study, therefore producing mixed economic intuition. Overall, this finding confirms that a frontier model that provides scope for unmeasured heterogeneity is likely to be preferable to one that does not.

The rank and median efficiency levels of the ‘true’ random effect model which somehow accommodates the time varying features and the time invariant unobserved heterogeneity in our panel dataset seems very intuitive. The overall average national efficiency of the 19SSA countries from 1960 to 2010 is 78.3% in the TRE model. Given that the overall median is 81.22% for the entire sample, the median of 80.0% for SSA countries indicate that, overall SSA is relatively not efficient. At the country level however, we note that some of the countries like South Africa, Mauritius are above the median and somehow efficient.

The findings show that countries and regions that are technically efficient will significantly boost TFP’s contributions to output per worker and as a result increase income levels. The inefficiency within the SSA region impedes the contributions of TFP to output per worker resulting in the poor economic performance and low incomes. These findings provide an evidence to support earlier studies on the significance of national efficiency to the understanding of the evolution of world income distribution across countries (see Prescott, 1998 and Jerzmanowski, 2007).

This is an unambiguous signal to policy managers that in order to increase output per worker, policies should be formulated to overcome the barriers to the absorption and effective utilisation of available resources and global technology in order to strongly enhance technical efficiency. Consecutively, to provide policy guidelines for policy makers in SSA with regards to the poor efficiency performance, it is important to further examine technical efficiency so as to establish how specific policy implications, for example, openness to trade, human capital, among others affect technical efficiency across countries in SSA.

APPENDICES

Table A1. List of Countries

Sub- Saharan Africa		
Cameroon	Mauritius	Uganda
Cote D'Ivoire	Mozambique	Zambia
Ethiopia	Nigeria	Zimbabwe
Ghana	Rwanda	
Kenya	Senegal	
Madagascar	Sierra Leone	
Malawi	South Africa	
Mali	Tanzania	

Table A1. List of Countries (Con't)

	Asia	
China	South Korea	Sri Lanka
Indonesia	Taiwan	
Malaysia	Thailand	
Phillipines	India	
Singapore	Pakistan	
	Latin America	
Argentina	Guatemala	Peru
Bolivia	Guyana	Trinidad and Tobago
Brazil	Haiti	Uruguay
Chile	Honduras	Venezuela
Colombia	Jamaica	
Costa Rica	Mexico	
Dominican Rep.	Nicaragua	
Ecuador	Panama	
El Salvador	Paraguay	
	OECD	
Australia	Germany	New Zealand
Austria	Great Britain	Norway
Belgium	Iceland	Portugal
Canada	Ireland	Spain
Denmark	Italy	Sweden
Finland	Japan	Switzerland
France	Netherlands	United States
	Others	
Algeria		
Egypt		
Iran		
Israel		
Jordan		
Morocco		
Tunisia		

Table A2. Summary Statistics

Variables	Mean	Std. Deviation	Min	Max
Log Real GDP	11.605	1.695	8.228	16.397
Log Capital stock	10.885	2.840	2.470	17.627
Log Labour force	15.348	1.512	11.994	20.461
Human capital	4.661	2.128	0.615	10.566

Table A3. Mean National Efficiency Levels using "True Random Effects" Specification (in Parenthesis) for Other Countries in the Sample.

	Asia	
China (0.83)	South Korea (0.94)	Sri Lanka (0.74)
Indonesia (0.78)	Taiwan (0.94)	
Malaysia (0.92)	Thailand (0.84)	
Phillipines (0.87)	India (0.77)	
Singapore (0.95)	Pakistan (0.71)	
	Latin America	
Argentina (0.83)	Guatemala (0.80)	Peru(0.81)
Bolivia (0.79)	Guyana (0.78)	Trinidad and Tobago (0.77)
Brazil (0.94)	Haiti (0.51)	Uruguay (0.80)
Chile (0.82)	Honduras (0.73)	Venezuela (0.76)
Colombia (0.83)	Jamaica (0.78)	
Costa Rica (0.77)	Mexico (0.95)	
Dominican Rep. (0.75)	Nicaragua (0.61)	
Ecuador (0.84)	Panama (0.78)	
El Salvador (0.81)	Paraguay (0.84)	
	OECD	
Australia (0.94)	Germany (0.95)	New Zealand (0.92)
Austria (0.92)	Great Britain (0.94)	Norway (0.95)
Belgium (0.95)	Iceland (0.88)	Portugal (0.85)
Canada (0.96)	Ireland (0.89)	Spain (0.88)
Denmark (0.94)	Italy (0.88)	Sweden (0.95)
Finland (0.95)	Japan (0.96)	Switzerland (0.94)
France (0.91)	Netherlands (0.95)	United States (0.97)
	Others	
Algeria (0.84)		
Egypt (0.82)		
Iran (0.86)		
Israel (0.95)		
Jordan (0.78)		
Morocco (0.89)		
Tunisia (0.85)		

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