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Relative Winners and Losers from Efficiency Spillovers in Africa with Policy Implications for Regional Integration

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Abstract

Studies that have analyzed the efficiency of developing countries have estimated non-spatial frontier models. We extend this approach by accounting for spatial dependence among African countries. In particular, we estimate a spatial Durbin stochastic production frontier model. We also make novel use of the efficiency scores from our spatial model to suggest a direction for regional integration policy for Africa that policy makers can consider. A previous suggestion to promote regional integration in Southern Africa has been to use South Africa as a regional integration hub and to encourage other countries in the region to improve economic links with the hub. We continue with this line of enquiry and although we conclude that there are currently no African countries that are ideal candidates to be a regional integration hub, we suggest three other countries that policy makers may consider using as hubs in the future. We therefore suggest that it would be prudent to consider implementing policies to expedite the readiness of these countries to act as integration hubs.

Key words: Stochastic frontier analysis (SFA); Spatial autoregression (SAR); Panel data; Asymmetric efficiency spillovers; Africa; Regional integration.

JEL Classification: C23; O19; O47; O55.

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1 Introduction

Promoting regional integration in Africa is a vehicle policy makers have used to, among other things, try and stimulate economic growth. The growth performance of African countries, however, has been poor for a sustained period which Easterly and Levine (1997) refer to as the 'African growth tragedy'. To illustrate, from the World Bank's World Development Indicators for the period $1980-2014$, average annual growth of real GDP per capita in Africa is a mere 0.27% compared to average annual growth of almost 7% for developing countries in East Asia and the Pacific. Consequently, it is almost certainly the case that sub-Saharan African countries will not have achieved a Millennium Development Goals (MDGs) target to halve the proportion of the population living below 1 U.S. dollar per day by 2015. In particular, Tahari *et al.* (2004) predict that an annual growth rate for sub-Saharan Africa of 3.5% over the period $1997-2002$, which was regarded as a growth recovery period, is less than half the rate needed to achieve the above MDGs poverty reduction target. In practice, despite a lot of effort to promote regional integration in Africa through the formation of the regional economic communities (RECs) and the Accra Declaration in 2002 to accelerate economic and political integration across the continent, progress on regional integration has been 'slow and difficult' (United Nations, 2011). Consequently, the regional integration process in Africa needs fresh impetus. This paper seeks to provide some direction in this regard.

This paper makes three contributions. Firstly, our study contributes to the small body of literature that focuses solely on analyzing the efficiency of African countries. Primarily studies analyze the efficiency of a small number of African countries as part of a wider efficiency analysis comprising developed and developing countries or exclusively developing countries from around the world (Badunenko and Romero-Ávila, 2013; Badunenko *et al.*, 2008; 2013; Henderson and Russell, 2005; Henderson and Zelenyuk, 2007; Henry *et al.*, 2009; Krüger, 2003; Mastromarco and Ghosh, 2009; Milner and Weyman-Jones, 2003). Sickles *et al.* (201**6**), however, argue against estimating the efficiency of countries from different income groups relative to a single best practice production frontier because these groups have separate production frontiers. In line with this, Badunenko *et al.* (2014) and Danquah and Ouattara (2015) are, to the best of our knowledge, the only studies that focus on benchmarking the efficiency of African countries against one another. That said, our data set on aggregate production of African countries is much more comprehensive. To illustrate, Danquah and Ouattara (2015) analyze the efficiency of 18 of the 49 sub-Saharan African countries, whereas our data set includes, among others, 44 sub-Saharan African countries. Secondly, all the above studies that analyze the efficiency of African countries estimate a non-spatial frontier model, whereas we account for spatial dependence in our modeling. We do this by applying a recent development in parametric spatial efficiency analysis (Glass *et al.*, 2016a, denoted GKSW from hereon) which involves estimating a spatial Durbin stochastic production frontier (SDPF) model. Thirdly, the efficiency estimates from our spatial stochastic frontier model are used in an innovative way to suggest a direction for regional integration policy for Africa that policy makers can consider.

The SPDF model that we estimate nests the spatial autoregressive (SAR) stochastic frontier model as it not only includes the SAR variable (or in other words the spatial lag of the dependent variable) which accounts for global spatial dependence (1st order through to $(N-1)$th order spatial interaction), but also spatial lags of the exogenous regressors which account for local spatial dependence (1st order spatial interaction).[1] Moreover, the model in GKSW extends a recent key development on spatial stochastic frontier modeling (Glass *et al.*, 2016b) by, among other things, accounting for unobserved heterogeneity via random effects. Another possible specification is the spatial error stochastic frontier model but we do not estimate this model because spatial error autocorrelation tends to be a rather ad hoc way of modeling global spatial dependence as the spillovers only relate to the random shocks.[2] In this paper we adopt a more general approach because it is well-established that the spatial Durbin specification nests the spatial error specification (LeSage and Pace, 2009). Also, the global spatial dependence that the SAR variable accounts for in spatial models such as the SDPF in GKSW has a clear economic interpretation as it can be related to the exogenous regressors through the calculation of the spillover elasticities, otherwise known as the indirect marginal effects. We discuss in detail these marginal effects further in the paper.

More generally, there is a small body of literature on spatial stochastic frontier modeling that adopts a different approach to the one we employ here. In this literature the fixed/random effects from a spatial panel data model are used to compute efficiency. The first such study was by Druska and Horrace (2004). By extending the non-frontier spatial error model for cross-sectional data in Kelejian and Prucha (1999) they introduce the GMM spatial error stochastic frontier model with fixed effects. Using the fixed effects they then apply the Schmidt and Sickles (1984) efficiency estimator which assumes a composed disturbance structure with idiosyncratic error and time-invariant inefficiency components. With this estimator, which has been shown to yield consistent estimates of time-invariant efficiency (Greene, 2008), for a concave frontier (i.e., a production, revenue or profit frontier) the unit with the largest fixed/random effect in the sample is assumed to be efficient and is placed on the frontier with an efficiency score of 1. Conversely, for a convex frontier (i.e., a cost frontier) the unit with the smallest fixed/random effect in the sample is placed on the frontier. The time-invariant efficiencies of the other units are then calculated relative to the best performing unit and reflect how far a unit is located

[1] Unlike the local spatial variables, the SAR variable is endogenous which we account for in the modeling.

[2] In a spatial error stochastic frontier model global spatial dependence would be accounted for using a spatial lag of the disturbance vector.

from the frontier. More recently, using a panel data SAR stochastic frontier model, Glass *et al.* (2013) compute time-variant efficiency by applying the Cornwell *et al.* (1990) time-variant extension of the Schmidt and Sickles (1984) efficiency estimator.[3]

In contrast to the spatial stochastic frontier models that compute efficiency using the fixed/random effects, we follow GKSW, Glass *et al.* (2016b) and numerous studies that estimate a non-spatial stochastic frontier model by making distributional assumptions to distinguish between the idiosyncratic error and time-variant inefficiency. This approach is appealing because computing efficiency using the fixed/random effects assumes that the best performing unit is efficient, whereas making distributional assumptions to compute efficiency is less restrictive because the best performing unit may or may not lie on the frontier. Furthermore, spatial stochastic frontier models that compute efficiency using fixed/random effects assume that all the latent heterogeneity is time-invariant inefficiency. In the spatial setting we distinguish not just between latent heterogeneity and time-variant inefficiency, which is common in the non-spatial stochastic frontier literature (Greene, 2005; Chen *et al.*, 2014; Tsionas, 2002), but also between latent heterogeneity and time-invariant inefficiency. Distinguishing between latent heterogeneity and both time-invariant and time-variant inefficiencies in a non-spatial setting has been introduced to the literature only recently (e.g. Filippini and Greene, 2016). Rigidities in assets and rigidities in the internal organization of production would be sources of time-invariant inefficiency and it would be reasonable to think that concurrent with these rigidities there could be managerial inefficiency which would be a source of time-variant inefficiency. Managerial inefficiency may vary over time because of, for example, the turnover of managerial staff with different skill sets.

A suggestion to promote regional integration in Southern Africa is to use the largest economy in the region (South Africa) as a regional integration hub and to encourage other countries in the region to enhance their trade links with the hub (Arora and Vamvakidis, 2005; African Development Bank, 2011). Since using a country as an economic centre to promote regional integration in Africa has been previously suggested we continue with this line of enquiry in this paper. In particular, although there are eight RECs in Africa only five are recognized by the World Trade Organization as being active in terms of the regional integration process and inter-REC trade (Hartzenberg, 2011). The five recognized RECs are: the Eastern African Community (EAC); the Economic Community of Central African States (ECCAS); the Southern African Development Community (SADC); the Common Market for Eastern and Southern Africa (COMESA); and the Economic

[3] Throughout this paper we focus solely on spatial stochastic frontier models that rely on an exogenous specification of the spatial interaction among the cross-sectional units by populating a spatial weights matrix. Mastromarco *et al.* (2016), on the other hand, estimate a common factors stochastic frontier model rather than a model that is based on a spatial weights matrix. They also then follow Cornwell *et al.* (1990) to propose an estimator of time-variant efficiency that accounts for cross-sectional dependence.

Community of West African States (ECOWAS).[4] On the basis of our empirical findings we suggest a small number of countries that policy makers may in the future consider as economic centres to promote regional integration. To this end an important feature of the model in GKSW that we draw on is the asymmetric flows of efficiency spillovers. In particular, as African countries can be seemingly quite independent of one another there are a number of cases where there are big inequalities in output per capita between countries in the same region. For example, Gabon and DR Congo are both members of the ECCAS REC and share a border with Congo, but over the period $1980-2011$ average annual real output per capita for Gabon was over 22 times that for DR Congo. The countries we suggest that policy makers may in the future consider as regional integration hubs are all therefore net exporters of efficiency within their respective RECs to guard against further inequality in output per capita between countries in the same region. The idea is that a programme of specific policies to promote regional integration would then be targeted at regional integration hubs. Although it is outside the scope of this paper to propose any specific regional integration policies that should be directed towards regional integration hubs, we provide some examples of the general form that these policies may take. Further work is needed to recommend the appropriate specific regional integration policies that should be targeted at regional integration hubs.

To provide an insight into our empirical findings, we note that even though it is common for African countries in the same region to be seemingly quite independent of one another, our preferred specification of the spatial interaction among the countries in our sample (i.e. our preferred spatial weights matrix) corresponds to the widest possible spatial interaction. This is because in our preferred spatial weights matrix each country interacts with every other country which suggests that there is widespread tacit spatial linkages at work among African countries. The implication from this finding is that there is an opportunity for progress on regional integration in Africa. The big challenge, however, is converting these tacit spatial linkages into the explicit dependence among countries that is associated with regional integration. Furthermore, based on our empirical analysis we make two suggestions about the direction of regional integration policy for Africa. First, our empirical analysis suggests that no African countries are currently suited to being regional integration hubs for the RECs. This implies that there could be a shortage of suitable candidates in the future, implying that policy makers may consider using a smaller number of hubs to promote wider regional integration beyond an individual REC. Second, we suggest three countries that policy makers may consider using as integration hubs in the future. As we conclude that all three countries are currently not ready to be an integration hub, we recommend that policy makers strive to accelerate

[4] Currently EAC has 5 members, ECCAS has 10, SADC has 15, COMESA has 19 and ECOWAS has 15. There are also some cases where a country is a member of more than one REC. Of the 47 countries in our sample there are 11 cases where a country is a member of two RECs and two cases where a country is a member of three. Burundi, for example, is a member of EAC, ECCAS and COMESA.

the readiness of these countries to act as hubs.

The remainder of this paper is organized as follows. In section 2 we set out the econometric and empirical methodology, which has four aspects. The first is the presentation of the random effects SDPF model. The second is a non-technical discussion of the pseudo maximum likelihood (PML) estimation procedure. The third is the testing methodology we use to establish whether the error structure of our SDPF model specification is appropriate for our empirical application. This involves testing to determine if the fitted model distinguishes between time-invariant inefficiency and latent heterogeneity and between time-variant inefficiency and the idiosyncratic error. The fourth is an explanation of the method to compute the asymmetric flows of efficiency spillovers to and from a country. In section 3 we describe the data set and in section 4 we present and discuss the findings from our empirical analysis focusing on how we use the efficiency spillovers to suggest a direction for regional integration policy in Africa that policy makers may consider. Section 5 concludes and suggests related areas for further work.

2 Empirical Methodology

2.1 Spatial Durbin Stochastic Production Frontier (SDPF) with Random Effects

The general form of our SDPF model with random effects, where lower case letters denote logged variables, is:

$$
\begin{aligned}
y_{it} = {} & \alpha + \varrho t + TL\left(x_{it}\right) + \gamma^{'} z_{it} + \zeta^{'} \sum_{j=1}^{N} w_{ij} x_{jt} + \xi^{'} \sum_{j=1}^{N} w_{ij} z_{jt} + \\
& \delta \sum_{j=1}^{N} w_{ij} y_{jt} + \kappa_i + v_{it} - \eta_i - u_{it}; \qquad (1) \\
\kappa_i & \sim N\left(0, \sigma_\kappa^2\right), \ \eta_i \sim N^{+}\left(0, \sigma_\eta^2\right); \\
v_{it} & \sim N\left(0, \sigma_v^2\right), \ u_{it} \sim N^{+}\left(0, \sigma_u^2\right); \\
i & = 1, ..., N; \ t = 1, ..., T.
\end{aligned}
$$

In each cross-section there are N units indexed $i = 1, ..., N$ that operate over T periods indexed $t = 1, ..., T$. Following the spatial econometrics literature we focus on large N and small T. y_{it} is the observation for output for the ith unit in time period t, α is the intercept and W_N is the pre-specified $(N \times N)$ exogenous spatial weights matrix of non-negative constants, w_{ij}. W_N represents the spatial arrangement of the cross-sectional units and also the strength of the interaction among the units and is often populated using some measure of geographical proximity. $\sum_{j=1}^{N} w_{ij} y_{jt}$ is the endogenous spatial lag of the dependent variable and δ is the SAR parameter. In addition, Eq. 1 requires three assumptions which are standard normalizations and regularity conditions from the spatial econometrics literature (e.g., Baltagi *et al.*, 2003). (i) The elements on the main diagonal of W_N are zero. (ii) The matrix $(I_N - \delta W_N)$ is non-singular and the parameter space of δ is $(1/g_{\min}, 1/g_{\max})$, where $g_{\min}$ and $g_{\max}$ are the most negative and most positive real characteristic roots of W_N, respectively, and I_N is the $(N \times N)$ identity matrix. (iii) The row and column sums of $\widetilde{W}_N$ and the matrix $\left(I_N - \delta \widetilde{W}_N\right)^{-1}$ are uniformly bounded in absolute value, where $\widetilde{W}_N$ is W_N before a normalization transformation. See section 3 for more details on the normalization transformations of $\widetilde{W}_N$ that we utilize in the empirical analysis. In particular, Assumption (i) rules out self-influence because a unit cannot be viewed as its own neighbor. Assumption (ii) ensures that the reduced form of Eq. 1 exists (see Eq. 3 for the reduced form of Eq. 1), where in the empirical analysis we compute asymmetric flows of efficiency spillovers for African countries using the reduced form of the SDPF model. As a result of Assumption (iii), the spatial process of the dependent variable is limited to a manageable degree as it has a fading memory (e.g. Kelejian and Prucha, 2001).

The spatial Durbin specification is a relatively general model specification because in addition to the SAR variable it includes spatial lags of the exogenous regressors. The spatial Durbin specification is therefore relatively data intensive so we model the effects of time using the relatively simple Hicks-neutral technical change specification, which we account for via the time trend, t, where ϱ denotes the associated regression parameter.[5] $TL(x_{it}) = \rho' x_{it} + \frac{1}{2} x_{it}' \Psi x_{it}$ represents the translog production technology, where x_{it} is a $(K \times 1)$ vector of observations for the inputs indexed $k = 1, ..., K$. ρ' is a $(1 \times K)$ vector of regression parameters and Ψ is a matrix of ψ regression parameters. Eq. 1 is therefore twice differentiable with respect to the inputs, where the associated Hessian is symmetric because of the symmetry restrictions that are imposed on Ψ i.e. $\psi_{1K} = \psi_{K1}$ (Christensen *et al.*, 1973). $\sum_{j=1}^{N} w_{ij} x_{jt}$ is a vector of observations for the spatial lags of the inputs and ζ' is the associated vector of regression parameters. For reasons of parsimony we do not include spatial lags of the squared input terms and input interaction terms. Since we do not include spatial lags of all the exogenous regressors Eq. 1 is strictly a partial SDPF, although to simplify the terminology from hereon we refer to Eq. 1 as an SDPF. Furthermore, z_{it} is a vector of observations for non-spatial regressors, $\sum_{j=1}^{N} w_{ij} z_{jt}$ is its spatial lag and γ' and ξ' are the associated vectors of regression parameters. z_{it}, $\sum_{j=1}^{N} w_{ij} x_{jt}$, $\sum_{j=1}^{N} w_{ij} z_{jt}$ and $\sum_{j=1}^{N} w_{ij} y_{jt}$ all shift the production frontier technology in Eq. 1.

Eq. 1 has a four component error structure, $\varepsilon_{it}^{*} = \varepsilon_i + \varepsilon_{it} = \kappa_i + v_{it} - \eta_i - u_{it}$,

[5] We omit the spatial lag of t for reasons of perfect collinearity because $W_N * t = t$ when W_N is row-normalized. We also omit $W_N * t$ when we use another normalization of $\widetilde{W}_N$ to maintain uniformity with the model specifications when W_N is row-normalized.

where $\varepsilon_i = \kappa_i - \eta_i$ is the time-invariant component and $\varepsilon_{it} = v_{it} - u_{it}$ is the time-variant component. Our model relies on κ_i, v_{it}, η_i and u_{it} being i.i.d. across i and t or just i as is appropriate, where distributional assumptions distinguish between each error component. v_{it} is the idiosyncratic error and as is standard when modeling unobserved heterogeneity using random effects, the unit specific effect, κ_i, is a time-invariant random error. η_i is time-invariant inefficiency (II) and u_{it} is time-variant inefficiency (VI). Both η_i and u_{it} are assumed to have a half-normal distribution which is a common distributional assumption for inefficiency in the stochastic frontier literature (e.g., Bos *et al.*, 2010a; 2010b; Greene, 2004).

For the corresponding non-spatial specification of Eq. 1 a one-step simulated maximum likelihood estimation procedure has been shown to be feasible (Filippini and Greene, 2016). For our spatial model in Eq. 1, however, rather than use a one-step simulated maximum likelihood estimator or a one-step Bayesian estimator, we use a simpler estimation procedure which can be easily applied more widely. This involves following GKSW and estimating our spatial model using a PML estimation procedure which, rather than using a one-step maximum likelihood (ML) estimator, involves estimating the model in steps using ML. In particular, our spatial model in Eq. 1 is estimated by maximizing three log-likelihood functions, one for each step. Step 1 estimates the non-frontier random effects spatial Durbin model which distinguishes between the time-invariant component of the composed error, ε_i, and the time-variant component, ε_{it}.[6] In step 1 we model latent heterogeneity using random effects rather than fixed effects because our estimation procedure relies on all four error components being i.i.d. which will not be the case with the fixed effects model if the fixed effects are correlated with the time-varying errors. Step 2 splits ε_{it} into its constituent parts, v_{it} and u_{it}, and step 3 splits ε_i into κ_i and η_i.

The multiplicative form of Eq. 1 is:

$$Y_{it} = \exp(\alpha) * \varrho \exp(t) * X_{it}^{\rho} * \left(X_{it}^{'} X_{it}\right)^{\frac{1}{2}\Psi} * Z_{it}^{\gamma} * \left(\sum_{j=1}^{N} w_{ij} X_{jt}\right)^{\zeta} * \left(\sum_{j=1}^{N} w_{ij} Z_{jt}\right)^{\xi} * \left(\sum_{j=1}^{N} w_{ij} Y_{jt}\right)^{\delta} * VE_{it} * IE_i * \exp(v_{it} + \kappa_i), \quad (2)$$

where VE_{it} is time-variant efficiency, IE_i is time-invariant efficiency, other upper case letters denote scalar observations of previously defined variables and everything else is as in Eq. 1. As a result of our SDPF having this multiplicative form, $VE_{it} = \exp(-\widehat{u}_{it})$

[6] Step 1 accounts for the endogeneity of the SAR variable as the step 1 log-likelihood function includes the scaled logged determinant of the Jacobian of the transformation from $\varepsilon_{it}^{\bullet}$ to $y_{it}^{\bullet}$, $T \log |I_N - \delta W_N|$, where $\varepsilon_{it}^{\bullet}$ and $y_{it}^{\bullet}$ are previous transformations of ε_{it}^{*} and y_{it}, respectively. As is standard in the spatial econometrics literature, the transformation from $\varepsilon_{it}^{\bullet}$ to $y_{it}^{\bullet}$ takes into account the endogeneity of the SAR variable (Anselin, 1988, pp. 63; Elhorst, 2009).

and $IE_i = \exp(-\widehat{\eta}_i)$. Productive units may of course lie below the concave production frontier because they are inefficient. Lower VI_{it} (II_i) will push VE_{it} (IE_i), which is bounded in the interval $[0, 1]$, closer to the upper bound. We use the classic Jondrow *et al.* (1982) method to compute the estimate of VI_{it}, $\widehat{u}_{it} = E(u_{it}|\varepsilon_{it})$, in step 2 using ε_{it} from step 1. We also use this method to compute the estimate of II_i, $\widehat{\eta}_i = E(\eta_i|\varepsilon_i)$, in step 3 using ε_i from step 1. Using VE_{it} and IE_i we compute combined time-variant efficiency, $CE_{it} = \exp[-(\widehat{\eta}_i + \widehat{u}_{it})] = IE_i * VE_{it}$, where CE_{it} is also bounded in the interval $[0, 1]$ and is time-variant due to VE_{it} being time-variant.

Testing the appropriateness of our model specification for our empirical application involves testing for the presence of each of the four error components (κ, v, η and u). In particular, this involves conducting the one-sided hypothesis test in Gouriéroux *et al.* (1982). The test statistic has an asymptotic distribution that is a mixture of chi-squared distributions, $\frac{1}{2}\chi^2(0) + \frac{1}{2}\chi^2(1)$. For $H \in \{\kappa, v, \eta, u\}$ rejection of the null, $\widehat{\sigma}_H^2 = 0$, in favor of the alternative hypothesis, $\widehat{\sigma}_H^2 > 0$, constitutes evidence of the presence of the error component.[7]

2.2 Asymmetric Flows of Efficiency Spillovers

LeSage and Pace (2009) demonstrate for models that contain the SAR variable such as Eq. 1 that the marginal effect for an exogenous regressor is a function of the SAR parameter. In particular, using the fitted parameters from a model such as Eq. 1 they suggest an approach to calculate direct, indirect and total elasticities.[8] Calculation of these elasticities is now standard in the applied spatial econometrics literature. Here, however, and in contrast to GKSW, we show how the calculation of direct, indirect and total elasticities is related to the approach to compute asymmetric flows of efficiency spillovers to and from a unit. Rewriting Eq. 1 in its reduced form, where we drop the i subscripts to denote successive stacking of cross-sections.

[7] Andrews (2001) derives another relevant approach to test for the presence of each component of our error structure. The test statistic he derives allows for, firstly, the possibility that the parameter value lies on the boundary of the parameter space under the null and, secondly, the possible presence of a nuisance parameter under the alternative hypothesis. The asymptotic distribution of this test statistic is not a chi-squared distribution and involves semi-parametric simulation.

[8] A direct elasticity is interpreted in the same way as an elasticity from a non-spatial model, although a direct elasticity takes into account feedback effects which occur via the spatial multiplier matrix. Feedback is the effect of a change in an independent variable of a particular unit which reverberates back to the same unit's dependent variable through its effect on the dependent variables of the other units in the sample. An indirect elasticity can be calculated in two ways yielding the same numerical value. This leads to two interpretations of an indirect elasticity: (i) average change in the dependent variable of all the other units in the sample following a change in an independent variable for one particular unit; or (ii) average change in the dependent variable for a particular unit following a change in an independent variable for all the other units in the sample. The total elasticity is the sum of the direct and indirect elasticities.

$$y_t = (I_N - \delta W_N)^{-1} \begin{pmatrix} \alpha\iota + \varrho t + \beta^{'}\tau_t + \gamma^{'} z_t + \zeta^{'} W_N x_t + \\ \xi^{'} W_N z_t + \kappa + v_t - \eta - u_t \end{pmatrix}, \tag{3}$$

where $(I_N - \delta W_N)^{-1}$ is the spatial multiplier matrix and ι is an $(N \times 1)$ vector of ones. τ_t is a vector of stacked observations for $TL(x_{it}) = \rho^{'} x_{it} + \frac{1}{2} x_{it}^{'} \Psi x_{it}$ or, in other words, a vector that includes stacked observations for x_{it} and $x_{it}^{'} x_{it}$. For simplicity the $\rho^{'}$ and Ψ translog parameters are collected in the vector of parameters $\beta^{'}$ in Eq. 3 and everything else is a previously defined for Eq. 1.

We set out the approach to calculate the direct, indirect and total elasticities at the sample mean for a first order input which we denote $x_{k,t}$. From the local spatial counterpart of Eq. 1 (i.e., Eq. 1 with the SAR variable omitted), which would capture only first order neighbor effects, using mean adjusted data all the fitted parameters from this local spatial model are elasticities. This is because at the sample mean the quadratic and interaction terms are zero. Extending this to Eq. 3 the fitted β and ζ parameters for $x_{k,t}$ and $W_N x_{k,t}$ can be used to directly calculate the direct, indirect and total elasticities for $x_{k,t}$ at the sample mean. Differentiating Eq. 3 with respect to $x_{k,t}$ yields the following matrix of direct and indirect elasticities for each unit, where the right-hand side of Eq. 4b is independent of the time index.

$$\begin{bmatrix} \frac{\partial y}{\partial x_{k,1}}, & \cdots & , \frac{\partial y}{\partial x_{k,N}} \end{bmatrix}_t = \begin{bmatrix} \frac{\partial y_1}{\partial x_{k,1}} & \cdots & \frac{\partial y_1}{\partial x_{k,N}} \\ \vdots & \ddots & \vdots \\ \frac{\partial y_N}{\partial x_{k,1}} & \cdots & \frac{\partial y_N}{\partial x_{k,N}} \end{bmatrix}_t \tag{4a}$$

$$= (I_N - \delta W_N)^{-1} \begin{bmatrix} \beta_{x_k} & \cdots & w_{1N}\zeta_{x_k} \\ \vdots & \ddots & \vdots \\ w_{N1}\zeta_{x_k} & \cdots & \beta_{x_k} \end{bmatrix}, \tag{4b}$$

where β_{x_k} and ζ_{x_k} denote the elements of the $\beta^{'}$ and $\zeta^{'}$ vectors which relate to x_k and $W_N x_k$.

Since Eq. 4b yields different direct and indirect elasticities for each unit, to facilitate interpretation LeSage and Pace (2009) suggest reporting a mean direct elasticity (average of the diagonal elements of Eq. 4b) and a mean indirect elasticity (this average spillover elasticity to a unit is the average row sum of the off-diagonal elements of Eq. 4b and is numerically the same as the average spillover elasticity from a unit which is the average column sum of the off-diagonal elements of Eq. 4b).[9] For variables such as the squared and interacted inputs whose spatial lags are omitted from Eq. 1, the mean direct, mean indirect and mean total elasticities are calculated using Eq. 4b but with the $w_{ij}\zeta$ off-

[9] We follow LeSage and Pace (2009) and compute the associated $t-$statistics by Monte Carlo simulation of the distributions of the mean direct, mean indirect and mean total elasticities.

diagonal elements set equal to zero by construction.

GKSW set out the methodology to compute direct, indirect and total efficiencies. Here we explain how their approach builds on the approach to calculate direct, indirect and total elasticities. To this end we begin with definitions of the direct, indirect and total efficiencies. Direct efficiency for a unit is interpreted in a same way as own efficiency from a non-spatial model. In contrast to own efficiency from a non-spatial or a spatial stochastic frontier model, direct efficiency is own efficiency plus efficiency feedback. Efficiency feedback is the component of a unit's direct efficiency which, due to the spatial multiplier matrix, $(I_N - \delta W_N)^{-1}$, has rebounded back to the unit having passed through 1st order and higher order neighbors. As was the case for an indirect elasticity, indirect efficiency can be interpreted in two ways: (i) the sum of the efficiency spillovers to a unit from all the other units in the sample; and (ii) the sum of efficiency spillovers from a unit to all the other units in the sample. As we show formally below and point to in the empirical analysis, when these two indirect efficiencies are averaged across the sample they will yield the same numerical value but they will be asymmetric for individual units. In the same way as a total elasticity is calculated, a unit's total efficiency is the sum of its direct and indirect efficiencies. Due to there being two asymmetric indirect efficiencies for a unit, there are two asymmetric total efficiencies for each unit. When the two total efficiencies are averaged across the sample, however, they yield the same numerical value. We now present these ideas formally where Dir, Ind and Tot denote direct, indirect and total.

From the reduced form of our model in Eq. 3 we recognize that $(I_N - \delta W_N)^{-1}\eta = \eta^{Tot}_{Imp}$ and $(I_N - \delta W_N)^{-1}u_t = u^{Tot}_{t,\,Imp}$, where η^{Tot}_{Imp} and $u^{Tot}_{t,\,Imp}$ are $(N \times 1)$ vectors of total II and total VI_t, respectively. Imp denotes that the inefficiency spillovers used in the calculation of these total inefficiency vectors are inefficiency spillovers which the ith unit implicitly imports from all the jth units in the sample for $i \neq j$. As a result of the multiplicative form of our model in Eq. 2 we can transform the above II^{Tot}_{Imp} and $VI^{Tot}_{t,\,Imp}$ vectors into the corresponding vectors of total efficiencies, $(I_N - \delta W_N)^{-1}\exp(-\eta) = IE^{Tot}_{Imp}$ and $(I_N - \delta W_N)^{-1}\exp(-u_t) = VE^{Tot}_{t,\,Imp}$. Moreover, since we have established above that own combined efficiency from Eq. 1 is $\exp[-(\eta + u_t)] = IE * VE_t = CE_t$ then $(I_N - \delta W_N)^{-1}\exp[-(\eta + u_t)] = CE^{Tot}_{t,\,Imp}$, where $CE^{Tot}_{t,\,Imp}$ is an $(N \times 1)$ vector of total CE_t. Thus $CE^{Tot}_{t,\,Imp}$ can be written in the following form and IE^{Tot}_{Imp} and $VE^{Tot}_{t,\,Imp}$ can also be written in the same form using similar expressions.

$$(I_N - \delta W_N)^{-1} \begin{pmatrix} CE_1 \\ \vdots \\ CE_N \end{pmatrix}_t = \begin{pmatrix} CE_{11}^{Dir} & + & \cdots & + & CE_{1N}^{Ind} \\ \vdots & + & \ddots & + & \vdots \\ CE_{N1}^{Ind} & + & \cdots & + & CE_{NN}^{Dir} \end{pmatrix}_t = \begin{pmatrix} CE_{Imp,\ 1}^{Tot} \\ \vdots \\ CE_{Imp,\ N}^{Tot} \end{pmatrix}_t, \tag{5}$$

where $CE_{t,\ ij}^{Dir}$ for $i = j$ on the main diagonal is direct CE of a unit, $CE_{t,\ ij}^{Ind}$ is the indirect CE spillover to the ith unit from the jth unit for $i \neq j$ and $CE_{t,\ Imp,\ i}^{Ind} = \sum_{j=1}^{N} CE_{t,\ ij}^{Ind}$ is the sum of indirect CE spillovers to the ith unit from all the jth units for $i \neq j$.

The column sums of the above components is the $(1 \times N)$ total CE vector, $CE_{t,\ Exp}^{Tot'} = \left(CE_{Exp,\ 1}^{Tot}, CE_{Exp,\ 2}^{Tot}, \ .\ .\ , CE_{Exp,\ N}^{Tot}\right)_t$, where Exp denotes that the indirect CE spillovers used in the calculation of $CE_{t,\ Exp}^{Tot'}$ are the CE spillovers that the ith units implicitly export to the jth unit for $i \neq j$. $CE_{t,\ Exp,\ j}^{Ind} = \sum_{i=1}^{N} CE_{t,\ ij}^{Ind}$ is the sum of indirect CE spillovers from all the ith units to the jth unit for $i \neq j$. $CE_{t,\ Imp,\ i}^{Tot}$ and $CE_{t,\ Exp,\ j}^{Tot}$ therefore measure a unit's CE across a system/network, where in the empirical analysis the system that we analyze is the African economic system.

In our empirical analysis W_N is asymmetric which is typical in empirical applications. If W_N is asymmetric, $(I_N - \delta W_N)^{-1}$ will be asymmetric resulting in $CE_{t,\ ij}^{Ind} \neq CE_{t,\ ji}^{Ind}$ in Eq. 5, which indicates that a unit implicitly imports and exports asymmetric indirect CE spillovers. Furthermore, Eq. 1 yields own IE, VE and CE that are directly comparable to the corresponding efficiencies from a non-spatial stochastic frontier model. The efficiencies from Eq. 1 therefore relate to an individual unit and do not include any efficiency spillovers across the system/network. In contrast, the direct, indirect and total IE, VE and CE efficiencies from the reduced form of our model in Eq. 3 all include some form of efficiency spillover. As we noted above, the own IE, VE and CE from Eq. 1 are all bounded in the interval $[0, 1]$. The lower bound of the direct, indirect and total IE, VE and CE from the reduced form of our model will of course also be 0. Other than that direct, indirect and total IE, VE and CE are unbounded. Direct, indirect and total IE, VE and CE, however, can be easily interpreted as they are percentages. This is because direct, indirect and total IE, VE and CE are scaled own IE, VE and CE. The magnitude of the scaling relates to the magnitude of the efficiency spillover that is included in the direct, indirect and total IE, VE and CE. If the magnitude of the efficiency spillover is sufficiently large a direct/indirect/total IE, VE or CE score will be greater than 1. If this is the case the efficiency spillover has pushed the unit beyond the best practice frontier for own efficiency from Eq. 1.

3 Data and Spatial Weights Matrices

We estimate Eq. 1 using twelve specifications of W. The data is a balanced panel comprising annual observations for 47 African countries for the period $1980 - 2011$ which constitutes rich data for an aggregate productivity study of Africa.[10] The data was primarily extracted from version 8.1 of the Penn World Table (Feenstra *et al.*, 2015), PWT8.1.

Output is output-side real GDP from PWT8.1, y (in 2005 million U.S. dollars at 2005 PPPs). As is recommended in the documentation which accompanies the preceding version of the Penn World Table, we use $rgdpo$ to analyze productivity across countries rather than expenditure-side real GDP or GDP at 2005 national prices (see Feenstra *et al.* 2013, pp. 31). x is a (2×1) vector of input levels. The first input is the labor input and is the number of people engaged from PWT8.1, x_1. Real capital stock at current PPPs from PWT8.1 is the second input, x_2 (in 2005 million U.S. dollars).[11,12]

z is a (11×1) vector of variables which together with the spatial lags of the first order inputs, Wx, the spatial lags of the z variables, Wz, and the SAR variable, Wy, shift the production frontier. Moreover, there is quite a large literature on the effect or lack of an effect of the weather on aggregate output (see Dell *et al.*, 2014, for a survey of this literature). We therefore include six weather variables using rich data from the Climatic Research Unit, University of East Anglia, UK: z_1 is average monthly cloud cover as a percentage which measures the duration of sunlight; z_2 is the total number of rainy days in a year which measures the frequency of rainfall; z_3 is total precipitation in a year which measures the level of rainfall; z_4 is average monthly temperature; z_5 is average monthly vapor pressure which measures humidity; and z_6 is the average monthly diurnal temperature range which measures the extent of extreme temperatures.[13] For

[10] Missing data did, however, result in the omission of seven countries from the analysis (Algeria, Comoros, Eritrea, Libya, Seychelles, Somalia and South Sudan). Unlike in the non-spatial setting, for spatial panels the asymptotic properties of estimators such as the PML estimator of Eq. 1 become problematic unless the reason why data are missing is known (Elhorst, 2009). For example, Pfaffermayr (2013) assumes that data are missing at random for an unbalanced spatial panel. We want to avoid making such an assumption for African countries so we use balanced panel data. This is because it is unlikely to be reasonable to assume that data across African countries are missing at random. Missing data for African countries may instead be correlated with the economic development of a country.

[11] Following the documentation which accompanies version 8.0 of the Penn World Table (Inklaar and Timmer, 2013, pp. 13) we use real capital stock at current PPPs rather than real capital stock at 2005 national prices (in 2005 million U.S. dollars).

[12] A number of studies that analyze the efficiency of African countries include human capital as an additional input. Here we face a trade-off between including human capital and the appropriateness of the specification of efficiency spillovers between African countries. This is because including human capital would involve substantially reducing the number of countries in our sample because of missing data. Omitting a substantial number of African countries from our sample would mean that countries' neighborhood sets (e.g., countries' contiguous neighbors) would not be reflective of African geography resulting in an inappropriate specification of efficiency spillovers. As other studies in the area have focused on the role of human capital we instead focus on the most appropriate specification of efficiency spillovers that the available data permits.

[13] See https://crudata.uea.ac.uk/cru/data/hrg/ to access the weather data we use.

more details on the weather data we use see Harris *et al.* (2014).[14]

To account for the agrarian share of land use data is obtained from the World Bank (World Development Indicators, WDI) on arable land share, z_7. Using Freedom House data we control for the effect of the political rights, z_8, and civil liberties, z_9, of individuals in a country.[15] To account for the effect of net trade openness, using data from PWT8.1 we include exports of merchandise minus imports of merchandise as a share of GDP, z_{10}. From WDI we obtain data on the share of the total population residing in urban areas, z_{11}, to account for the degree of urbanization in a country. In table 1 we present the summary statistics for our data set. All the appropriate continuous variables are logged then mean adjusted so the first order own parameters from the non-spatial translog stochastic frontier and the first order direct, indirect and total parameters from the spatial translog stochastic frontiers can be interpreted as elasticities at the sample mean.

[Insert table 1 about here]

We use six specifications of W before normalization which are all based on inverse distances between country centroids. Since all the specifications of W are based on geographical location rather economic distance (e.g., trade flows or input-output tables) the spatial weights are exogenous.[16] For countries which are made up of a number of territories (e.g., Djibouti, Equatorial Guinea and Guinea) we calculate the distance to the centroid of the primary territory. This is so the centroid of a country is on dry land and therefore a point within a country's territory. Specifically, the six specifications of W before normalization are based on inverse distances to the nearest $3-7$ countries (denoted $W_{3Near} - W_{7Near}$) and inverse distances between centroids of all the countries (denoted W_{All}). Furthermore, in applied spatial econometrics a contiguity based specification of W is frequently used. We do not use a contiguity based W because some countries in the sample are islands (Mauritius, Madagascar, Cape Verde, and São Tomé and Príncipe) and therefore have no contiguous neighbors which violates the requirement for the construction of W that each unit has at least one neighbor.

In total we use twelve normalized specifications of W. Six of these specifications are denoted $W^{Row}_{3Near} - W^{Row}_{7Near}$ and W^{Row}_{All}, where the superscript denotes that W has been

[14] When we estimate the corresponding non-spatial specification of Eq. 1 using standard software that routinely drops collinear variables, none of the weather variables were dropped. We therefore include all the weather variables and their spatial lags in our program to estimate the SDPF model.

[15] Freedom House categorize the political rights and civil liberties of individuals in a country in integers from 1 (most freedom) to 7 (least freedom). For Namibia a small amount of political rights and civil liberties data are missing from $1980-1988$. We therefore estimated this missing data using the average annual rate of change across the sample from 1989 back to 1980.

[16] At present too much data is missing to specify W for African countries using input-output tables or trade flows. Over time this data will become available and it will be possible to construct an economic distance based specification of W. To account for the endogenous spatial weights in such a specification, the ML estimator that we use in step 1 should be replaced by the spatial instrumental variable estimator in Kelejian and Piras (2014).

normalized to have row sums of unity. Using a row-normalized W facilitates interpretation of the parameter estimates because row-normalization preserves the scaling of the data. As a result, for a particular country the SAR variable will be a weighted average of the dependent variable for the countries in its neighborhood set. When an inverse distance based $\widetilde{W}$ is row-normalized spillovers are inversely related to the relative distance between the units. On one hand this is reasonable because distance here is being viewed as a relative measure which will vary from country-to-country depending on how isolated a country is from other countries in Africa. On the other hand, it could be argued this is unreasonable because the information on absolute distance between countries is lost by row-normalizing. To address this issue the six remaining specifications of W are normalized by the largest eigenvalue of $\widetilde{W}$ and are denoted $W^{Eig}_{3Near} - W^{Eig}_{7Near}$ and W^{Eig}_{All}. This normalization does not change the proportional relationship between the spatial weights in the corresponding $\widetilde{W}$, so spillovers are inversely related or the absolute distance between countries.

4 Discussion of the Empirical Findings

This section comprises four parts. (i) The discussion in 4.1 of the parameter estimates from the fitted Eq. 1 using our preferred specification of W. (ii) The discussion in 4.2 of the own IE, VE and CE scores from our preferred spatial stochastic frontier model. (iii) An analysis in 4.3 of the direct, indirect and total CE scores from our preferred spatial model. (iv) The discussion of the five recognized RECs in 4.4 regarding how we use the indirect efficiency exports for individual member countries to identify the principal exporter(s) of efficiency to the other members of the REC. From a policy perspective, the principal exporters of efficiency within the RECs informs which countries we suggest policy makers consider employing as future economic performance hubs to promote regional integration.

4.1 Estimated Models

Following the spatial analysis in Pfaffermayr (2009) model selection is based on the Akaike information criterion (AIC). The AIC favors the W^{Row}_{All} SDPF over the other eleven SDPF models, the non-spatial stochastic production frontier (NSPF) and the W^{Row}_{All} SAR stochastic production frontier (SARPF). The W^{Row}_{All} SARPF is the W^{Row}_{All} SDPF with the spatial lags of the exogenous regressors (i.e., the local spatial variables) omitted and the only difference between the twelve SDPF models is the specification of W. Our preference for the W^{Row}_{All} SDPF specification over the W^{Row}_{All} SARPF highlights the importance of the local spatial variables in the former. This is apparent from the estimation results in table 2 for our preferred W^{Row}_{All} SDPF model, where we also report in table 3 the estimation results for the corresponding NSPF and the W_{All}^{Row} SARPF to analyze the implications of model specification.[17] To illustrate, it is evident from table 2 that a number of the local spatial lagged variables in the fitted W_{All}^{Row} SDPF are significant at the 5% level or lower (spatial lags of the labor input, Wx_1, capital input, Wx_2, arable land share, Wz_7, and political rights, Wz_8). Also, although it is common for African countries in the same region to be seemingly quite independent of one another suggesting that explicit spatial linkages among African countries in a region are often tenuous, since W_{All}^{Row} is preferred in our analysis we posit that there is widespread implicit spatial linkages at work across Africa. This suggests that the prospects for regional integration in Africa are encouraging. This is because there is potential for the widespread implicit spatial linkages that we observe here to lead to a substantial rise in the explicit spatial interaction among African countries in the same region that is associated with regional integration. In tables 4 and 5 we present the direct, indirect and total elasticities from the W_{All}^{Row} SDPF and W_{All}^{Row} SARPF models, respectively.

[Insert tables $2-5$ about here]

As the applied spatial econometrics literature now recognizes, the SAR parameter, δ, in SAR and spatial Durbin models is not a spillover elasticity. Spillover elasticities from SAR and spatial Durbin models are the indirect elasticities, which as is apparent from Eq. 4b, are a function of δ, among other things. An estimate of δ, however, does have a meaningful interpretation as it represents the degree of SAR dependence across the countries. From tables 2 and 3 we can see that the estimates of the δ parameters from the W_{All}^{Row} SDPF and the W_{All}^{Row} SARPF are 0.33 and 0.51, respectively, both of which are significant at the 0.1% level. This indicates that both models capture non-negligible positive SAR dependence. That said, the estimate of δ from the W_{All}^{Row} SARPF model is much larger than that from the W_{All}^{Row} SDPF which suggests that the omission of the local spatial variables from the W_{All}^{Row} SARPF model results in δ being substantially overestimated and the degree of global spatial dependence being erroneously inflated.

In line with production theory, the own input elasticities at the sample mean from the NSPF in table 3 are positive, which is not always the case in the literature on the aggregate productivity of developing countries. The direct input elasticities at the sample mean in tables 4 and 5 from the W_{All}^{Row} SDPF and W_{All}^{Row} SARPF are also consistent with production theory as they too are positive. Moreover, the own/direct input elasticities at the sample mean from the NSPF, W_{All}^{Row} SDPF and W_{All}^{Row} SARPF are all significant at the 0.1% level. In each case, these own/direct elasticities suggest increasing returns to scale of the order of 1.15 and $t-$tests reveal that these returns are significantly greater than 1

[17] As is the case with the standard non-spatial non-frontier panel data random effects model, the θ parameter in the reported NSPF, W_{All}^{Row} SARPF and W_{All}^{Row} SDPF models is the weight which is attached to the cross-sectional component of the data.

at the 1% level or lower. Since compared to previous studies of the aggregate productivity of African countries our rich data set includes quite a lot more small countries which have small capital stocks, we posit that we observe increasing own/direct returns to scale at the sample mean because the capital productivity of these small countries is relatively high. This is because, other things being equal, these small countries will be much further away from the point where diminishing marginal returns to capital sets in.

Our fitted models would seem to suggest that a significant negative own/direct time parameter (see tables $3-5$) has contributed to the low total factor productivity (TFP) that has hindered Africa. This evidence of technological regress may be interpreted as counterintuitive but it is, nevertheless, in line with the findings from a number of studies in the area such as Krüger (2003) for sub-Saharan African countries. Collier and Gunning (1999) offer a range of reasons for the slow growth of Africa, some of which may have resulted in technological regress. These include, among others, civil warfare and political turmoil which are frequently observed phenomena across Africa. Looking ahead to our efficiency analysis, from the NSPF, W_{All}^{Row} SDPF and W_{All}^{Row} SARPF models we find that there is, on average, non-negligible combined inefficiency which fits with the relatively low TFP of African countries, as Jerzmanowski (2007) and Prescott (1998) conclude that differences in efficiency explain most of the differences in TFP across countries.

Interestingly, the indirect labor elasticity from the preferred W_{All}^{Row} SDPF is non-negligible and negative but only significant at the 10% level. This negative indirect elasticity is interesting as this finding has yet to be reported in the literature on the aggregate productivity of African countries. The indirect labor elasticity, however, from the W_{All}^{Row} SARPF is positive, non-negligible and significant at the 1% level. We observe contrasting indirect labor elasticities from the W_{All}^{Row} SARPF and W_{All}^{Row} SDPF because the former omits the spatial lag of the labor input which has a significant negative effect. Drawing on the interpretation of negative spatial parameters in the spatial econometrics literature as evidence of competition (e.g., Kao and Bera, 2013), we interpret the significant negative coefficient on the spatial lag of the labor input in the fitted W_{All}^{Row} SDPF as evidence of macroeconomic competition among African countries. This negative relationship is conceivable as it fits with the seeming lack of cohesion between African countries because of, among other things, slow progress on regional integration.

The indirect capital elasticity from the W_{All}^{Row} SDPF is positive, non-negligible and significant. Importantly this suggests that, on average, an African country's output will rise following an increase in the capital stock of the other African countries because of positive capital productivity spillovers. A possible mechanism here is that an African country's output increases because of greater demand for its exports from other African countries fuelled by the increases in their capital stocks. As a result of the direct and indirect capital elasticities from the W_{All}^{Row} SDPF, the total capital elasticity from this model is also positive, non-negligible and significant. In addition, we find that the total labor elasticity from the W_{All}^{Row} SDPF is not significant at nominal levels. This is because the direct and indirect labor elasticities have offsetting effects on the total elasticity, which is another interesting finding that has not been reported in the literature and offers a further reason for the low TFP across Africa.

Considering now some of the results for the z variables which have a substantive effect on the best practice frontier. From the preferred W_{All}^{Row} SDPF model the direct net trade openness (z_{10}) elasticity is non-negligible and the direct urbanization (z_{11}) elasticity is very large. In both cases these elasticities are significant and, as we would expect, they are both positive. In addition, the direct political rights (z_8) effect from the W_{All}^{Row} SDPF is negative, as we would expect, and significant. Interestingly, all the direct, indirect and total weather ($z_1 - z_6$) elasticities from the W_{All}^{Row} SDPF are not significant. In line with a substantive strand of the literature on the effect of the weather on economic activity, we posit that the weather elasticities from the W_{All}^{Row} SDPF are not significant because we have controlled for institutional quality via the political rights variable (e.g., Acemoglu *et al.*, 2001; Rodrik *et al.*, 2004). This strand of literature argues that evidence of a significant negative (positive) effect on economic activity from a rise in temperature (precipitation) from studies that do not control for national characteristics such as institutional quality is because of a spurious relationship between the weather and institutional quality.

4.2 Own Time-Variant, Time-Invariant and Combined Technical Efficiencies

In table 6 we present from the NSPF, W_{All}^{Row} SARPF and the preferred W_{All}^{Row} SDPF the average own VE, IE and CE across the sample. Also in table 6 we present average own VE, IE and CE for the individual countries and the corresponding average efficiency rankings. The sample average own VE (IE) from the NSPF, W_{All}^{Row} SARPF and W_{All}^{Row} SDPF are 0.877 (0.802), 0.874 (0.679) and 0.875 (0.704), respectively. As we would expect these findings indicate that there is substantial own VI and II for the sample average country from all three models. These results also suggest that the magnitude of the sample average own VE is robust to whether we control for global SAR dependence and also local spatial dependence in the case of the W_{All}^{Row} SDPF. In contrast, it is evident for our application that not controlling for global SAR dependence or global SAR dependence and local spatial dependence leads to a non-negligible overestimate of average own IE across the sample. The sample average own CE scores from the NSPF, W_{All}^{Row} SARPF and W_{All}^{Row} SDPF are 0.703, 0.594 and 0.617, respectively, where any differences between these average own CE estimates is due to the above differences in average own IE.

[Insert table 6 about here]

When we carry out on the fitted NSPF, W_{All}^{Row} SARPF and W_{All}^{Row} SDPF models the one-sided hypothesis test in Gouriéroux *et al.* (1982) of the null, $\widehat{\sigma}_H^2 = 0$, for $H \in \{\kappa, v, \eta, u\}$, in each case we reject the null in favor of the alternative hypothesis, $\widehat{\sigma}_H^2 > 0$, at the 5% level or lower. This supports the four component error structure that we employ for the fitted NSPF, W_{All}^{Row} SARPF and W_{All}^{Row} SDPF models. In summary, in line with the above own VE and IE scores for the sample average country from the NSPF, W_{All}^{Row} SARPF and W_{All}^{Row} SDPF, the one-sided test results for u and η for these models indicate the presence of VI and II.

The average own CE score for a country is particularly informative as it provides a much more complete picture of economic performance than the own VE or own IE score. This is because own CE is own VE and own IE combined. Focusing initially therefore on the average own CE rankings for the individual countries in table 6. The countries towards the top and bottom of the average own CE rankings from the NSPF, W_{All}^{Row} SARPF and W_{All}^{Row} SDPF is persuasive. For Liberia, DR Congo, Nigeria and Tanzania the average own CE rankings from the NSPF, W_{All}^{Row} SARPF and W_{All}^{Row} SDPF are consistently low. For Liberia this can be attributed to two civil wars ($1989 - 1996$ and $1999 - 2003$) that collectively span over half the length of our study period. The consistently low average CE rankings for DR Congo can be attributed to the exploitation of its natural stock of minerals (see Ross, 2003, for discussion of this natural resource curse in DR Congo) and the turbulence associated with civil wars, weak institutions and corruption. For example, there was a civil war in DR Congo from $1997 - 2003$ and violent conflicts have continued to persist with armed groups controlling regional areas.

The pervasive empirical evidence of a natural resource curse in Nigeria (e.g. Gylfason, 2001; Mehlum *et al.*, 2006; Sala-i-Martin and Subramanian, 2013) is consistent with its low average own CE ranking. Consequences of the natural resource curse in Nigeria include the weakening of institutions and the fuelling of corruption (Robinson *et al.*, 2006). In particular, Hall *et al.* (2010) find that weak institutions have a negative impact on growth and productivity during a period of capital expansion. This is because there is a tendency for the accumulated capital stock to be used for rent-seeking and in unproductive activities. For Angola, which produces less oil than Nigeria but is nevertheless still a large oil producing country, we find from the NSF, W_{All}^{Row} SARPF and W_{All}^{Row} SDPF that the average own CE rankings are higher than we observe for Nigeria but still quite low. A natural resource curse could also conceivably be a key driver of the average own CE rankings for Angola. In contrast, if there is a natural resource curse in countries such as Sudan and Equatorial Guinea it is not having a large detrimental impact as their average own CE rankings are high. This would suggest that any natural resource curse in these countries is relatively small which is consistent with Sudan and Equatorial Guinea being much smaller oil producing countries than Nigeria and Angola. For Tanzania we posit that the low average own CE rankings are because historically its economy has been far less open and diversified than, for example, the other economies in the EAC. This is evident because up until recently foreign investors, especially multinational firms, were virtually excluded from participating in core economic activities in Tanzania due to the socialist-leaning ideology in the country.

From the NSPF, W_{All}^{Row} SARPF and W_{All}^{Row} SDPF models the average own CE rankings are high for Mauritius and Zimbabwe. First impressions may suggest this is surprising for Zimbabwe but as we will see closer analysis reveals that it is not unreasonable. In a recent non-spatial stochastic frontier analysis of aggregate production in Africa, Danquah and Ouattara (2015) also find that Mauritius is highly efficient. We would expect a high average own CE ranking for Mauritius because it is the most successful economy in sub-Saharan Africa in terms of manufacturing exports per capita (Teal, 1999; Soderbom and Teal, 2003). Teal (1999) attributes this export performance to Mauritius having the best macroeconomic environment, the best trained work force and the most efficient firms in sub-Saharan Africa.

Despite the economic instability in Zimbabwe in recent times due to hurried land reforms, macroeconomic imbalances, hyperinflation and currency crises, in line with the high average CE rankings that we observe for Zimbabwe, Danquah and Ouattara (2015) also find that Zimbabwe is highly efficient. For the earlier part of our sample and the latter portion we offer different reasons for our high average CE rankings for Zimbabwe. For the earlier part of our sample that precedes the recent economic instability in Zimbabwe, we suggest that Zimbabwe is highly efficient because historically it had high manufacturing exports per capita (Wood and Jordan, 2000). For the second part of our sample that covers the recent instability, we argue that Zimbabwe is highly efficient because whilst its real capital stock was falling its real GDP was rising. To illustrate, our data set indicates that Zimbabwe's real capital stock shrunk dramatically by 81% over the period $1996-2010$, whereas over the same period its real GDP almost doubled.

More generally, the magnitudes of the average own VE scores for individual countries from the NSPF, W_{All}^{Row} SARPF and W_{All}^{Row} SDPF exhibit little variation between the countries. This indicates that the variation in the average own CE scores between the countries is due to the variation between their average own IE scores. We can see from table 6 though that the variation in the average CE scores between the countries is more reasonable from the W_{All}^{Row} SARPF and our preferred W_{All}^{Row} SDPF specification as the variation is wider than we observe from the NSPF. This highlights the importance of accounting for spatial dependence in our analysis.

4.3 Direct, Indirect and Total Combined Technical Efficiencies

Recapping, the direct IE, VE and CE scores from the reduced form of the SDPF in Eq. 3 are the own IE, VE and CE scores from the SDPF in Eq. 1 plus efficiency feedback.

Efficiency feedback is a particular form of efficiency spillover and is the component of a unit's direct efficiency which via the spatial multiplier matrix, $(I_N - \delta W_N)^{-1}$, passes through a unit's 1st order and higher order neighbors and rebounds back to the unit. Indirect IE, VE and CE refers to the sum of the efficiency spillovers which a unit imports (exports) from (to) the other units in the sample. Total IE, VE and CE are the sum of the corresponding direct and indirect IE, VE and CE scores. We focus on direct, indirect and total CE because as we noted above with reference to own CE, unlike IE and VE, CE provides a much more complete picture of economic performance. From the reduced form of our preferred W_{All}^{Row} SDPF model we report in table 7 average direct, indirect and total CE scores across the sample. In addition, from the reduced form of the W_{All}^{Row} SDPF model we also report in table 7 average direct, indirect and total CE scores and the associated rankings for the five highest ranked and the five lowest ranked countries.

[Insert table 7 about here]

The sample average direct CE from the reduced form of the W_{All}^{Row} SDPF is 0.621 which is very similar to the average own CE across the sample of 0.627 from Eq. 1. This similarity indicates that the efficiency feedback component of average direct CE across the sample is very small and negative. Finding that the average CE feedback component is small is in line with the small feedback elasticities in the spatial non-frontier literature (e.g., Autant-Bernard and LeSage, 2011).

It is evident from table 7 that the indirect CE spillovers that the sample average country exports and imports are symmetric. As the indirect CE spillovers that the sample average country imports and exports are in both cases 0.300, we conclude that the reduced form of the W_{All}^{Row} SDPF yields non-negligible estimates of these spillovers, which highlights the importance of accounting for spatial dependence in our efficiency analysis. At the level of an individual country, the indirect CE spillovers that a country exports and imports are asymmetric. For example, we can see from table 7 that the average indirect CE that The Gambia imports is 0.289 compared to its average indirect CE exports of 0.517. Since from the reduced form of the W_{All}^{Row} SDPF the indirect CE spillovers that the sample average country implicitly imports and exports are symmetric, the corresponding sample average total CE scores are also symmetric. This is evident because the sample average total CE scores from the reduced form of the W_{All}^{Row} SDPF are both 0.921. Moreover, since for an individual country the average indirect CE spillovers that it imports and exports are asymmetric, its corresponding average total CE scores are also asymmetric. From table 7, for example, using the average indirect CE imports to The Gambia its average total CE is 1.041, whereas using its average indirect CE exports yields a much higher average total CE for The Gambia of 1.270.

Turning now to a more detailed discussion of the average indirect CE spillovers for individual countries. We focus on the average indirect CE spillovers that individual countries implicitly export for two reasons. First, we can see from table 7 that the range of the average indirect CE spillovers that the countries implicitly export $(0.152 - 0.517)$ is much wider than the range of the average indirect CE spillovers that they import $(0.288 - 0.310)$. Second, it is the indirect CE exports from a country that benefit other countries and can therefore be used to incentivize regional integration in Africa. From table 7 we can see that, on average over the study period, the four largest largest exporters of CE to the other countries in the sample are: 1. The Gambia; 2. Togo; 3. Rwanda; and 4. Senegal. Interestingly, according to the 2014 Human Development Index, HDI, all four countries are in the lowest category of the index (i.e., the fourth) with low human development (United Nations, 2015). The fifth largest exporter of CE, Equatorial Guinea, is towards the bottom of the third category of the 2014 HDI with medium human development.

It is evident from table 7 that, on average over the study period, the five smallest exporters of CE are: 47. DR Congo; 46. Cape Verde; 45. Madagascar; 44. Mauritius; and 43. Tunisia. We posit that there are different reasons that explain these findings. The explanations we provide are, firstly, that DR Congo is a very poor country with the lowest average real GDP per capita in our sample. Secondly, some of these countries are island economies (Cape Verde, Mauritius and Madagascar) which inhibits their interaction with other countries in the sample. Thirdly, some of the countries are in the second/third category in the 2014 HDI with high/medium human development (Cape Verde, Mauritius and Tunisia). This is due to, among other things, prospering tourism so the development of these countries is relatively independent of other countries in the sample. There is little incentive therefore for these countries to have a relatively high degree of interaction with other African countries via large indirect CE exports. Fourthly, interaction between Tunisia and the sub-Saharan African countries that make up the vast majority of our sample is likely to be inhibited by cultural differences. This is consistent with a lot of empirical evidence suggesting that countries trade more with one another if they are culturally similar (e.g., Felbermayra *et al.*, 2010; Guiso *et al.*, 2006). Moreover, the above explanation for Tunisia can also be used to explain the low average indirect CE export rankings for Egypt and Morocco (42 and 40, respectively, from the reduced form of the W_{All}^{Row} SDPF).

It has been suggested that the country with the largest economy in Southern Africa (South Africa) should be used as an economic centre to promote integration among countries in the region (Arora and Vamvakidis, 2005; African Development Bank, 2011). Since our preferred SDPF model employs W_{All}^{Row}, which suggests that the tacit spatial dependence among African countries extends well beyond localized tacit dependence, a possible related policy might be to use a number of the largest economies in Africa as economic centres to foster widespread integration across the continent. We suggest that such a proposal would be ill-advised even though our preferred W_{All}^{Row} SDPF model suggests that tacit spatial dependence extends across Africa. This is because from the reduced form of our preferred model we find that the five largest economies in our sample in terms of average real GDP (1. South Africa; 2. Egypt; 3. Nigeria; 4. Morocco; and 5. Tunisia) are net importers of average CE. To illustrate, for the five largest economies in our sample average net CE exports range from $-0.11 - (-0.04)$, indicating that net imports of average CE can be non-negligible. Our findings therefore suggest that using the countries with the largest economies in Africa as economic centres to foster integration across the entire continent would promote more output inequality.

In contrast, from the reduced form of the W_{All}^{Row} SDPF there are number of countries that are net exporters of average CE to other African countries. On average, the five largest net exporters of CE are: 1. The Gambia (0.228); 2. Rwanda (0.148); 3. Togo (0.143); 4. Equatorial Guinea (0.140); and 5. Senegal (0.128). These net exports of CE are non-negligible so in theory if these five countries were used as economic centres to promote integration across Africa there would be an incentive to integrate with these countries. In practice, however, this integration is unlikely to come to fruition because of the reluctance of other African countries to integrate with these five countries. This is because integration with four of these five countries (The Gambia, Rwanda, Togo and Senegal), in particular, is unlikely to be an attractive proposition for other African countries as these four countries are all in the lowest category of the 2014 HDI with low human development. In addition, although Equatorial Guinea is in the penultimate category of the 2014 HDI with medium human development and it has the fifth largest average real GDP per capita in our sample, it is not a viable economic centre to promote widespread integration across Africa because its economy is relatively small.[18]

Since our results suggest that using the largest economies as economic centres to promote widespread integration across Africa would promote more output inequality and we made a case that using the largest net exporters of CE as economic centres to foster integration across Africa was not viable, we conclude that policy makers have followed the right course of action by pursuing more focused integration at the regional level. As we noted in the opening section of this paper, however, there has only been limited progress on regional integration in Africa which suggests that it would be worth considering a revised policy. In the next part of our empirical analysis we therefore focus on how our results may be used to inform a revised policy on regional integration in Africa.

[18]To demonstrate, average real GDP for Equatorial Guinea over our sample is in the bottom quartile.

4.4 Policy Implications for Regional Integration in Africa

The aim is to suggest for consideration by policy makers at least one country as an economic hub for each REC to facilitate regional integration. Furthermore, all the countries we suggest as hubs are net exporters of CE to the other members of the REC in an attempt to foster more income equality in a region. The approach we propose to identify the countries we suggest as hubs is based on non-hub members of a REC having an incentive to integrate with the relevant hub because the hub is net exporter of CE to the other members of the REC. To help us suggest countries as hubs for policy makers to consider, in figures $1-5$ we present for each member country of the five active RECs (COMESA, ECOWAS, SADC, ECCAS and EAC) net CE exports to other members of the REC from the reduced form of the W_{All}^{Row} SDPF model.

[Insert figures $1-5$ about here]

The three largest net exporters of CE within each REC are as follows. Within COMESA they are: 1. Rwanda (0.083), 2. Burundi (0.045) and 3. Zimbabwe (0.044); within ECOWAS they are: 1. The Gambia (0.115), 2. Togo (0.053) and 3. Senegal (0.045); within SADC they are: 1. Zimbabwe (0.067), 2. Botswana (0.030) and 3. Swaziland (0.021); within ECCAS they are: 1. Equatorial Guinea (0.043), 2. Gabon (0.020) and 3. Burundi (0.019); and finally, within EAC they are: 1. Rwanda (0.031), 2. Burundi (0.007) and 3. Uganda (-0.006).

As a country must be a net exporter of CE to other members of the REC for us to suggest the country as a regional integration hub for consideration by policy makers, this rules out the possibility of us suggesting Uganda as a hub for EAC. Moreover, none of the three largest net exporters of CE within each REC are among the three largest African economies in our sample (1. South Africa; 2. Egypt; and 3. Nigeria). Specifically, South Africa's net exports of CE within SADC is -0.007, Egypt's net exports of CE to other members of COMESA is -0.029 and Nigeria's net exports of CE within ECOWAS is -0.051. This suggests that using the largest economies in Africa as economic centres to promote regional integration would contribute to more output inequality in a region. Our results suggest this would particularly be the case if Nigeria was used as a regional integration hub.

To fix ideas, for us to suggest a country as a regional integration hub for consideration by policy makers, in addition to the country being a net exporter of CE to other members of the REC, relative to other African countries it will be characterized by a large economy, high living standards and a high level of human development to provide other countries in the REC with an incentive to integrate with it. In our view it is clear that a number of the largest net exporters of CE to other REC members are not suitable candidates to be regional integration hubs. This is for a number of reasons. It can be because the country's economy is relatively small which includes: Rwanda (32); Burundi (38); The Gambia (42); Togo (35); Swaziland (39); and Equatorial Guinea (37), where the average real GDP ranks over our sample are in parentheses. It can be because living standards in the country are relatively low which refers to: Rwanda (34); Burundi (45); and Togo (31), where the average real GDP per capita ranks over our sample are in parentheses. Also, it can be because the country is well inside the bottom category of the 2014 HDI with low human development which corresponds to: Rwanda; Burundi; The Gambia; Togo; and Senegal.

On the basis of our empirical results we conclude that there are currently no clear cases where an African country should be employed as a regional integration hub, either now or in the future. This suggests that formulating regional integration policy for Africa is difficult and consequently it is understandable why progress on regional integration in Africa has failed to meet expectations. As there are just three remaining countries that we suggest policy makers may consider using as regional integration hubs in the future, we conclude that there is a lack of possible candidates to be integration hubs for the RECs. In light of this, we suggest that policy makers should be aiming for wider regional integration beyond individual RECs. The three remaining countries, which are among the three largest net exporters of CE within at least one REC, are: Botswana; Zimbabwe; and Gabon. There are clear drawbacks with the candidacy of all three countries, which is the reason why in our opinion they are currently not suited to being integration hubs, although we believe there is an opportunity for these countries to become better suited to the role in the future. To prevent the drawbacks with these three countries undermining any future role as an integration hub, policies should first be adopted to better prepare them for the role.

On one hand, Gabon and Botswana are appealing as regional integration hubs as other countries will have an incentive to integrate with them because they have relatively high living standards (highest and fourth highest average real GDP per capita in our sample, respectively) and they are at the top or close to the top of the penultimate category of the 2014 HDI with medium human development. On the other hand, other countries may not have a sufficient incentive to integrate with Botswana and Gabon because their economies are not among the largest in Africa. This is evident because in our sample Botswana and Gabon's average real GDP are ranked 18th and 21st, respectively. We suggest therefore that to better prepare Botswana and Gabon for possible future roles as integration hubs, policies are presently needed to stimulate the size of their economies. Stimulating the size of their economies also has the potential to make Botswana and Gabon larger net exporters of CE.

Zimbabwe is obviously not currently a viable potential integration hub because of the ongoing economic and political instability in the country. If economic and political stability in Zimbabwe is restored we can envisage a situation where there is an opportunity for Zimbabwe to be a key integration hub. This is because Botswana and Zimbabwe could form a pair of neighboring integration hubs that together are able to fully realize the potential for regional integration in Southern Africa. Zimbabwe is a very interesting case because despite the ongoing economic and political instability in the country, we suggest that it is still worthwhile policy makers considering Zimbabwe as an integration hub in the future as it is one of the three largest net exporters of CE within the COMESA and SADC RECs. Other African countries are also likely to have an incentive to integrate with Zimbabwe because, despite the ongoing economic and political instability, its economy is relatively large (with the sixth highest average real GDP in our sample) and its relative living standards are reasonably high (with the ninth highest average real GDP per capita in our sample). Moreover, one can envisage Zimbabwe being an even larger net exporter of CE within the COMESA and SADC RECs if economic and political stability is restored in the country.

Looking ahead to a possible situation where policy makers have identified the countries that will act as economic centres to promote regional integration in Africa. Once the policy makers have identified the countries that will serve as integration hubs for Africa the idea is that specific regional integration policies will be targeted at the hubs. These specific policies are to enable other countries in a region to improve their economic links with the integration hub. As the integration hub will be a net exporter of CE, other countries in the region will benefit from improved economic links with the hub as these improved links will lead to less output inequality in the region. It is outside the scope of this paper to suggest any specific regional integration policies that should be directed towards integration hubs. Determining specific regional integration policies that should be targeted at integration hubs is therefore an important area for further work. We do, however, provide some examples of the general form that these policies may take which are as follows. (i) Incentives to promote capital flows from an integration hub to other countries in the region as there is a lot of empirical evidence which suggests that foreign direct investment (FDI) has a positive effect on economic growth in the host country (e.g., Barrell and Pain, 1997; Basu *et al.*, 2003). (ii) Transport infrastructure projects that improve accessibility to the integration hubs because using spatial econometric methods studies have found that investment in transport infrastructure has broader positive productivity effects that extend beyond the territory where the infrastructure investment occurs (Cohen and Morrison Paul, 2004; Cohen, 2010). (iii) Promoting the expansion of the integration hub's financial intermediaries in other countries in the region as there is a large literature which finds that banking and financial development leads to a rise in economic growth (e.g., Bonfiglioli, 2008; Ahmed, 2016). Such an expansion of a hub's financial intermediaries will lead to new financial capital channels that can stimulate economic growth of other countries in the region. This is because these new channels can be used to finance production and trade through goods being purchased in one country and being paid for in another.

5 Concluding Remarks and Further Work

As there is only a very small body of literature that focuses solely on analyzing the efficiency of African countries and data quality and its availability for African countries is improving all the time, there is scope for a lot more related work on Africa. Further related work is of paramount importance because economic performance has a key role to play in improving human development in Africa. In summary, the contributions of this paper are threefold. First, as we use a richer data set than previous related studies this enabled us to include substantially more African countries in our efficiency analysis. Second, previous related studies estimate non-spatial frontier models, whereas we extended this approach by accounting for spatial dependence among African countries. In particular, we applied a recent development by GKSW to estimate a spatial Durbin stochastic production frontier model with random effects. Third, we made novel use of the efficiency spillovers from our empirical analysis to suggest a possible revised direction for regional integration policy for Africa that policy makers may consider. This is because there is a need to inject fresh impetus to the regional integration process in Africa because economic growth in Africa is lagging well behind growth of developing countries in East Asia and the Pacific. Also, big inequalities continue to persist between some African countries in the same region.

Since a policy suggestion has been to use a country as an economic centre to promote regional integration in Africa (Arora and Vamvakidis, 2005; African Development Bank, 2011), we continued with this line of enquiry in this paper. In summary, on the basis of our empirical analysis we make two suggestions about regional integration policy for Africa that policy makers may consider. First, as our empirical findings suggest that no countries are currently suited to being regional integration hubs for the RECs, which implies that there is likely to be a shortage of suitable candidates in the future, we suggest that policy makers may consider using a smaller number of economic centres to promote wider regional integration beyond an individual REC. Second, we suggest three African countries which in our opinion have the potential to be viable integration hubs in the future. As there are currently non-negligible drawbacks associated with employing any of these countries as an integration hub, to avoid these drawbacks undermining any future role as a hub, we suggest that policy makers consider policies to improve the preparedness of these countries to act as hubs.

Looking ahead to a possible point in time where policy makers have settled on a small number of African countries to act as economic centres to promote regional integration. Having computed the efficiency spillovers between countries in a region and used the method we propose to identify the countries that will serve as integration hubs, the idea is that a programme of specific policies to promote regional integration would then be targeted at the hubs. Although it was outside the scope of this paper to suggest any specific regional integration policies that may be directed towards hubs, we provided some examples of the general form that these policies may take e.g., incentives to promote the flow of FDI from an integration hub to other countries in the region. In addition, since our study is the first to apply the GKSW methodology to inform the selection of countries to serve as regional integration hubs there is scope for wider application of our approach to, for example, countries in Latin America and the Caribbean, which is another case where regional integration needs stimulating (IMF, 2015). Also, the GKSW methodology could be applied at the sub-national level to NUTS II regions in Europe to aid integration at the regional level between long-standing members of the EU and countries that have joined the EU relatively recently.

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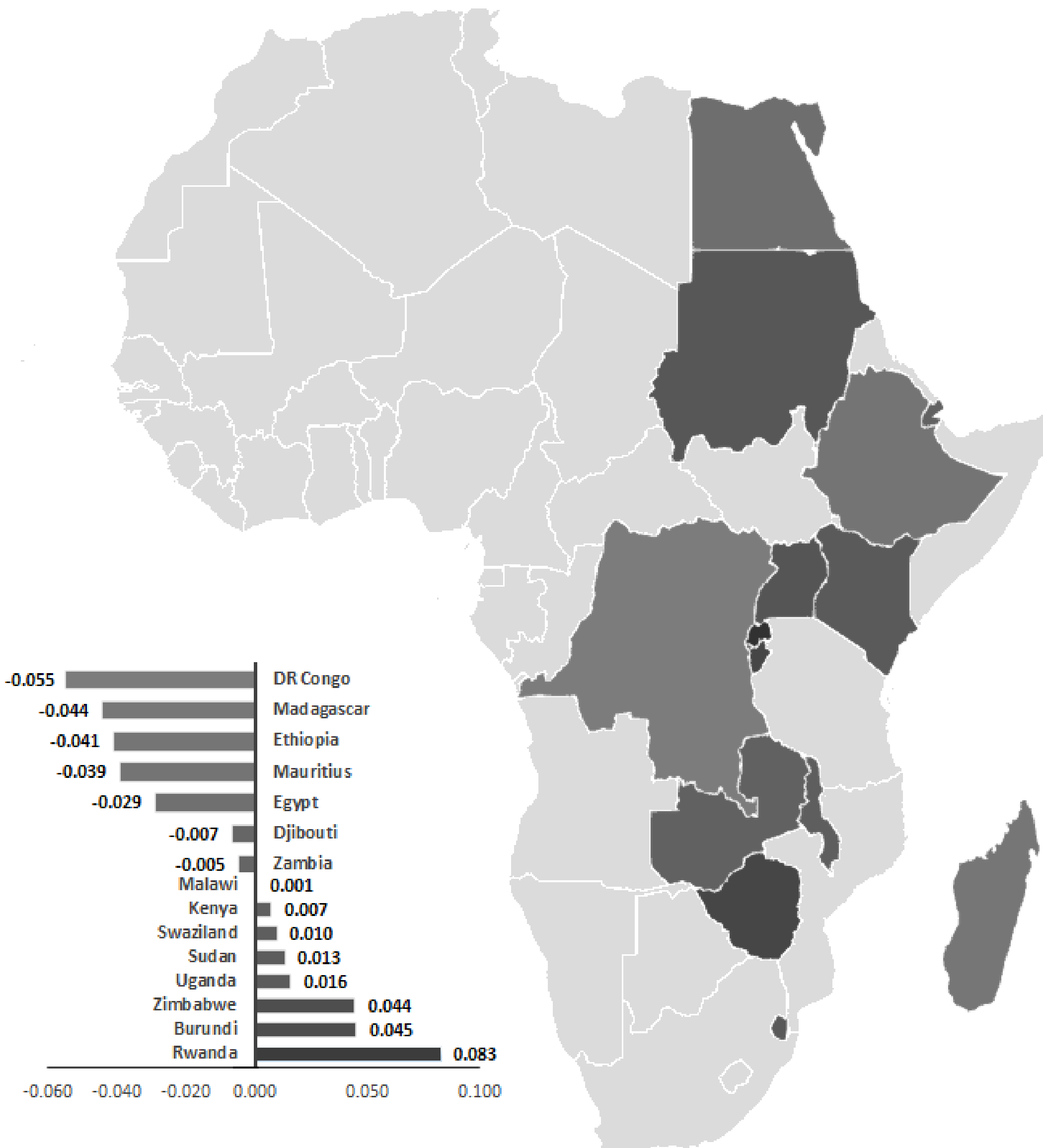

Figure 1: Net exports of combined efficiency within COMESA

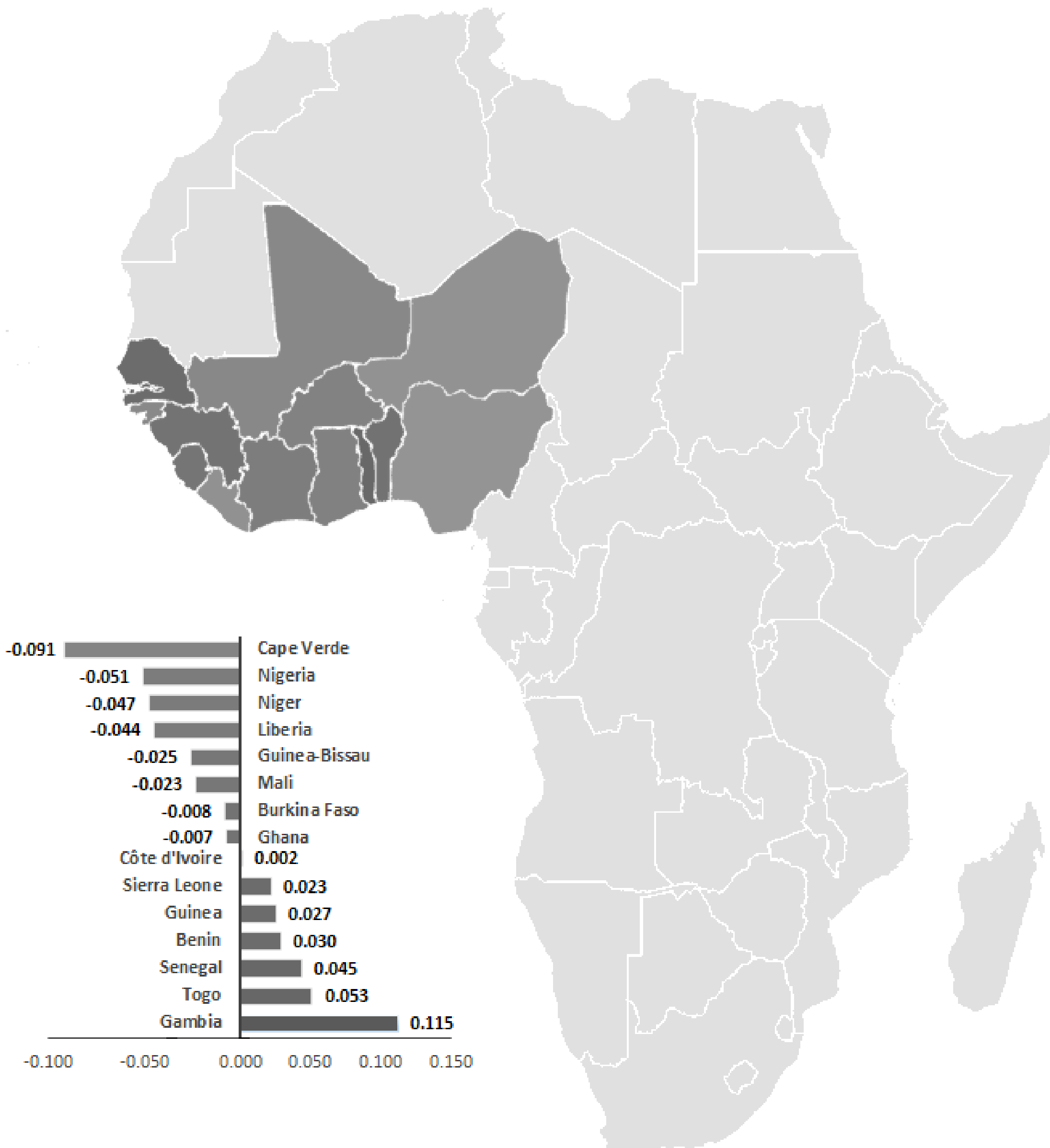

Figure 2: Net exprots of combined efficiency within ECOWAS

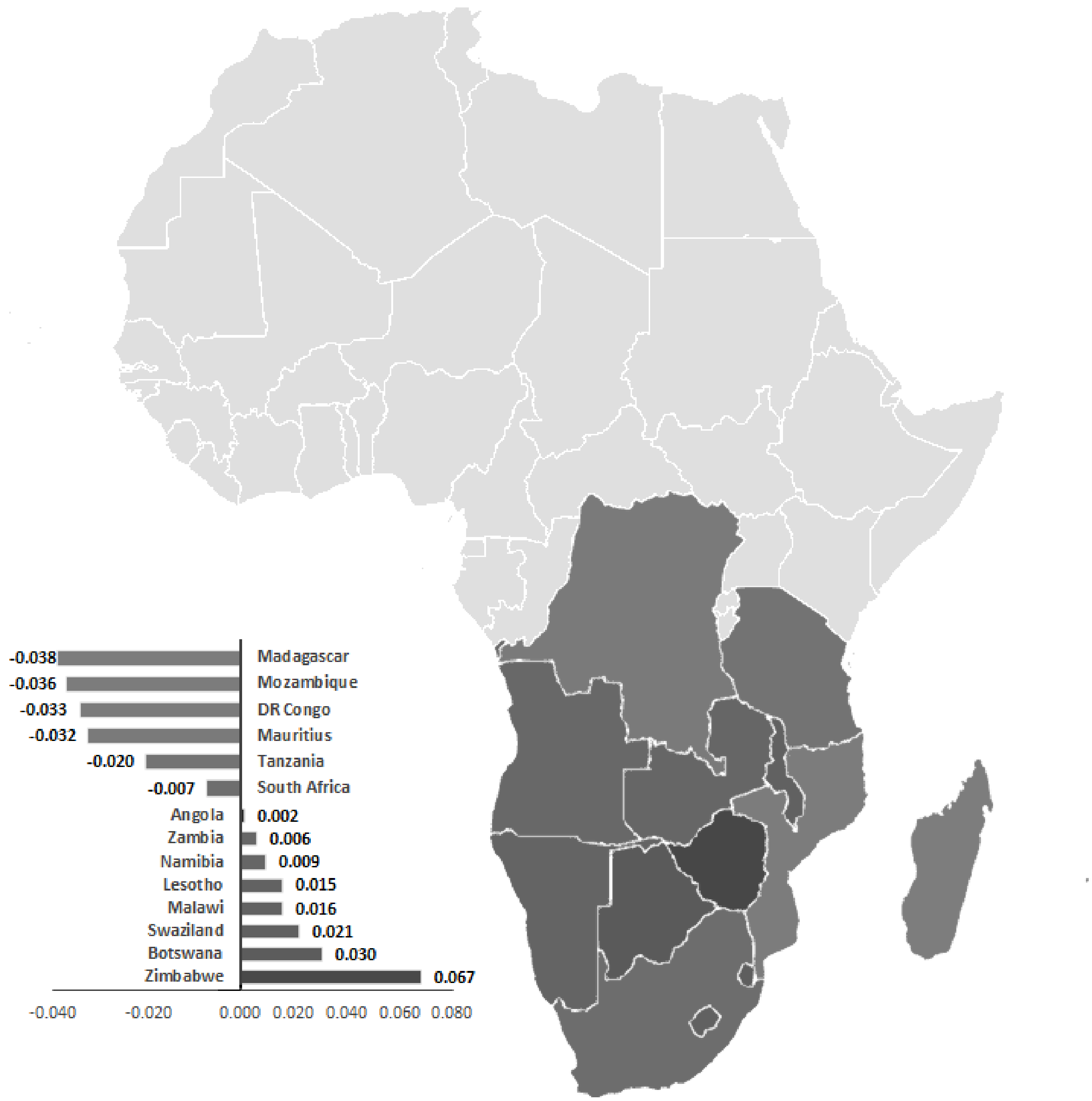

Figure 3: Net exports of combined efficiency within SADC

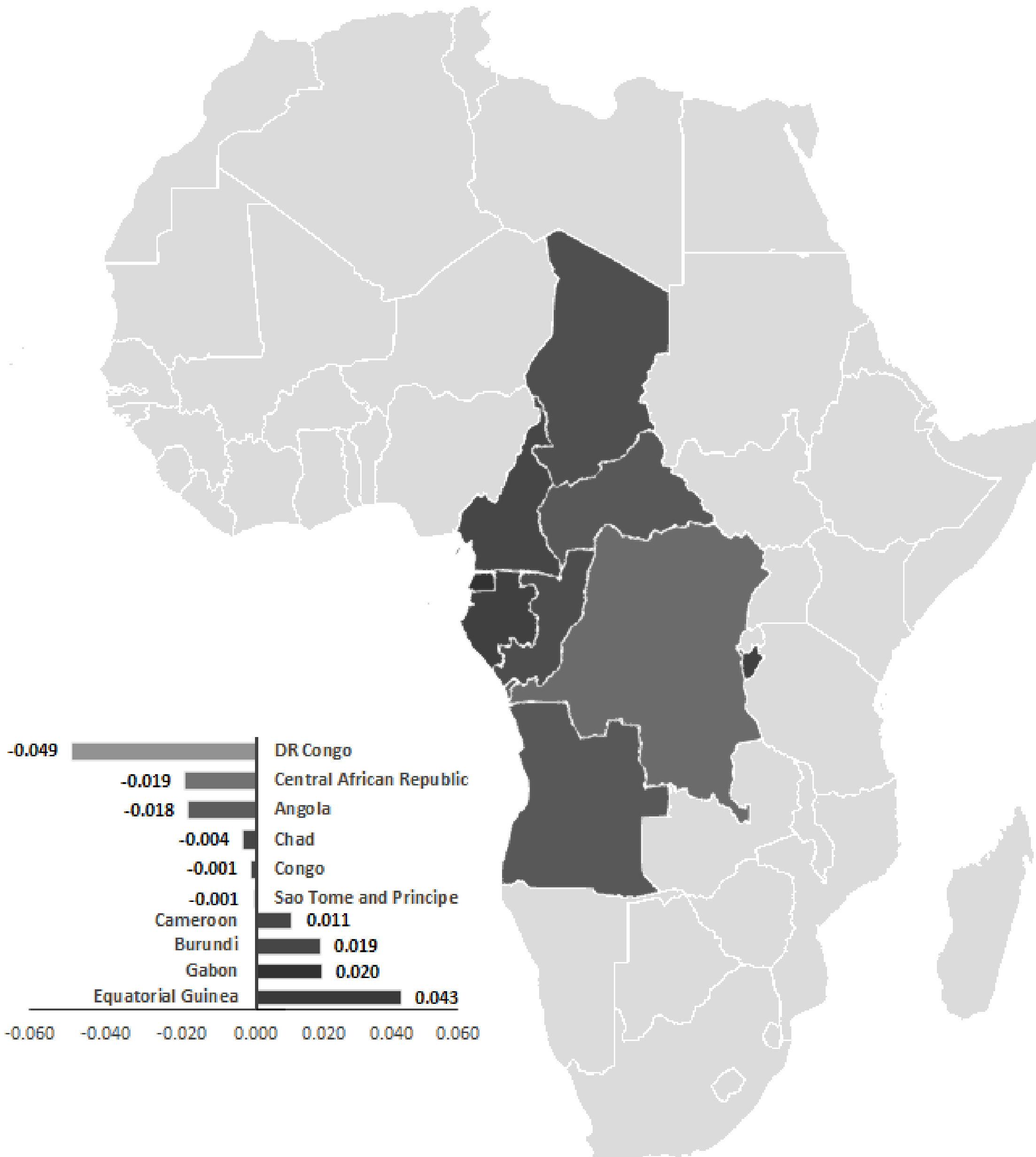

Figure 4: Net exports of combined efficiency within ECCAS

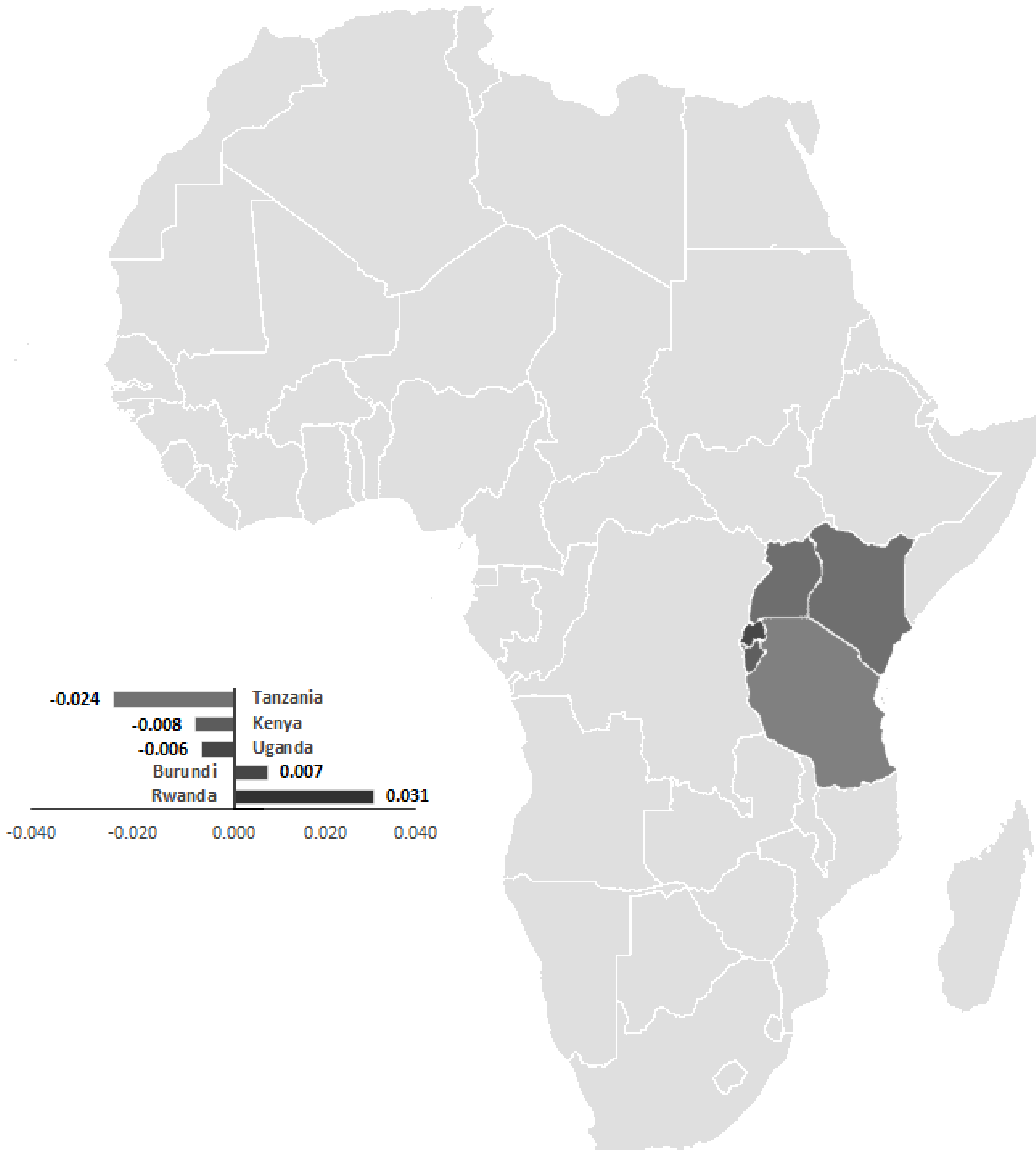

Figure 5: Net exports of combined efficiency within EAC

Table 1: Summary statistics

	Variable	Mean	St. Dev.	Min	Max
Real GDP (2005 million U.S. dollars at 2005 PPPs)	y	$31,283$	$68,479$	122	$527,565$
Number of people engaged (millions)	x_1	5.48	7.39	0.03	50.63
Real capital stock (2005 million U.S. dollars at current PPPs)	x_2	$52,853$	$111,770$	96	$978,195$
Cloud cover (%)	z_1	0.54	0.17	0.19	0.94
Annual number of rainy days	z_2	92.8	58.1	2.7	305.8
Annual precipitation (millimeters, mm)	z_3	1005.8	633.8	25.9	3332.9
Annual mean temperature (°C)	z_4	24.2	3.5	11.1	29.8
Annual mean vapour pressure (hectopascal, hPa)	z_5	19.6	4.8	7.7	28.4
Diurnal temperature range (°C)	z_6	11.9	2.4	5.5	16.6
Arable land share	z_7	0.12	0.12	0.00	0.49
Political rights ranking	z_8	4.89	1.79	1	7
Civil liberties ranking	z_9	4.70	1.44	1	7
Exports of merchandise minus imports of merchandise as a share of GDP i.e. net trade openness	z_{10}	-0.05	0.18	-0.91	0.93
Urbanization (%)	z_{11}	0.35	0.16	0.04	0.86

Table 2: Estimated preferred spatial Durbin stochastic production frontier model

			W_{All}^{Row} SDPF		
	Coeff	t-stat		Coeff	t-stat
x_1	0.61^{***}	11.04	Wx_1	-0.69^{*}	-2.30
x_2	0.55^{***}	34.60	Wx_2	0.26^{**}	2.69
x_1^2	0.10^{***}	6.62	Wz_1	1.08	0.88
x_2^2	0.02^{***}	3.51	Wz_2	0.06	0.16
x_1x_2	-0.09^{***}	-5.62	Wz_3	-0.21	-1.02
t	-0.02	-1.86	Wz_4	-2.07	-1.01
z_1	0.33	0.76	Wz_5	0.70	0.47
z_2	0.02	0.17	Wz_6	1.00	0.97
z_3	0.01	0.10	Wz_7	3.07^{**}	3.03
z_4	0.64	1.13	Wz_8	0.39^{**}	3.16
z_5	-0.60	-1.44	Wz_9	-0.17	-1.10
z_6	-0.31	-1.13	Wz_{10}	-0.02	-0.07
z_7	-0.09	-0.34	Wz_{11}	-0.26	-0.27
z_8	-0.07^{*}	-2.44	Constant	-1.59^{*}	-2.39
z_9	0.02	0.36	Wy	0.33^{***}	5.08
z_{10}	0.65^{***}	10.93	$\log_{10}\theta$	-2.38^{***}	-15.82
z_{11}	1.34^{***}	7.31			
	Parameter	SE		Parameter	SE
σ_v	0.20	0.01	σ_κ	0.36	0.02
σ_u	0.18	0.02	σ_η	0.49	0.04
LL			-18.55		
AIC			105.10		

SDPF denotes spatial Durbin stochastic production frontier model.
*, ** and *** denote statistical significance at the 5%, 1% and 0.1% levels, respectively.

Table 3: Estimated non-spatial and spatial autoregressive stochastic production frontier models

	NSPF			W_{All}^{Row} SARPF	
	Coeff	t-stat		Coeff	t-stat
x_1	0.59^{***}	11.14	x_1	0.63^{***}	11.62
x_2	0.56^{***}	34.30	x_2	0.54^{***}	34.57
x_1^2	0.11^{***}	6.98	x_1^2	0.10^{***}	6.54
x_2^2	0.04^{***}	5.50	x_2^2	0.02^{***}	3.44
x_1x_2	-0.11^{***}	-6.69	x_1x_2	-0.09^{***}	-5.44
t	-0.01^{***}	-7.02	t	-0.03^{***}	-13.07
z_1	0.57	1.58	z_1	0.46	1.31
z_2	0.10	1.12	z_2	0.08	0.89
z_3	-0.04	-0.70	z_3	-0.02	-0.33
z_4	0.68	1.38	z_4	0.72	1.47
z_5	-0.88^{*}	-2.40	z_5	-0.69	-1.90
z_6	-0.25	-0.96	z_6	-0.22	-0.87
z_7	-0.14	-0.52	z_7	-0.31	-1.23
z_8	-0.05	-1.50	z_8	-0.07^{*}	-2.49
z_9	-0.01	-0.26	z_9	0.01	0.20
z_{10}	0.63^{***}	10.12	z_{10}	0.64^{***}	10.81
z_{11}	1.14^{***}	6.07	z_{11}	1.26^{***}	6.94
Constant	-0.82^{***}	-3.76	Constant	-0.72^{***}	-3.35
θ	0.78^{***}	16.78	Wy	0.51^{***}	12.12
			$\log_{10}\theta$	-2.39^{***}	-16.35
	Parameter	SE		Parameter	SE
σ_v	0.21	0.01	σ_v	0.21	0.01
σ_u	0.17	0.02	σ_u	0.18	0.02
σ_κ	0.42	0.02	σ_κ	0.35	0.02
σ_η	0.30	0.09	σ_η	0.55	0.04
LL	-99.81		LL	-37.19	
AIC	239.62		AIC	116.37	

NSPF denotes non-spatial stochastic production frontier model.
SARPF denotes spatial autoregressive stochastic production frontier model.
*, ** and *** denote statistical significance at the 5%, 1% and 0.1% levels, respectively.

Table 4: Marginal effects from the preferred spatial Durbin stochastic production frontier model

		SDPF W_{All}^{Row}					
		Elasticity	t-stat			Elasticity	t-stat
x_1	*Direct*	0.60^{***}	12.72	z_4	*Direct*	0.58	0.99
	Indirect	-0.75	-1.70		*Indirect*	-2.73	-0.98
	Total	-0.16	-0.35		*Total*	-2.15	-0.79
x_2	*Direct*	0.56^{***}	30.75	z_5	*Direct*	-0.56	-1.31
	Indirect	0.63^{***}	5.09		*Indirect*	0.67	0.34
	Total	1.18^{***}	9.01		*Total*	0.10	0.05
x_1^2	*Direct*	0.10^{***}	6.19	z_6	*Direct*	-0.30	-1.21
	Indirect	0.05^{**}	3.06		*Indirect*	1.39	0.88
	Total	0.15^{***}	5.46		*Total*	1.09	0.69
x_2^2	*Direct*	0.03^{***}	3.52	z_7	*Direct*	-0.04	-0.14
	Indirect	0.01^{**}	2.65		*Indirect*	4.45^{**}	2.87
	Total	0.04^{***}	3.45		*Total*	4.41^{**}	2.74
x_1x_2	*Direct*	-0.09^{***}	-5.22	z_8	*Direct*	-0.07^{*}	-2.56
	Indirect	-0.04^{**}	-2.99		*Indirect*	0.52^{**}	2.69
	Total	-0.14^{***}	-4.84		*Total*	0.45^{*}	2.23
t	*Direct*	-0.02	-1.67	z_9	*Direct*	0.03	0.67
	Indirect	-0.01	-1.58		*Indirect*	-0.23	-1.02
	Total	-0.03	-1.70		*Total*	-0.20	-0.89
z_1	*Direct*	0.35	0.75	z_{10}	*Direct*	0.65^{***}	10.57
	Indirect	1.84	1.24		*Indirect*	0.34	1.06
	Total	2.18	1.59		*Total*	0.99^{**}	3.00
z_2	*Direct*	0.01	0.16	z_{11}	*Direct*	1.34^{***}	7.04
	Indirect	0.12	0.25		*Indirect*	0.18	0.12
	Total	0.14	0.28		*Total*	1.52	1.03
z_3	*Direct*	0.00	0.02				
	Indirect	-0.32	-1.07				
	Total	-0.32	-1.05				

SDPF denotes spatial Durbin stochastic production frontier model.
*, ** and *** denote statistical significance at the 5%, 1% and 0.1% levels, respectively.

Table 5: Marginal effects from a spatial autoregressive stochastic production frontier model for comparison purposes

		SARPF W_{All}^{Row}					
		Elasticity	t-stat			Elasticity	t-stat
x_1	*Direct*	0.64^{***}	13.65	z_4	*Direct*	0.70	1.32
	Indirect	0.64^{***}	5.16		*Indirect*	0.70	1.27
	Total	1.28^{***}	8.50		*Total*	1.39	1.31
x_2	*Direct*	0.55^{***}	31.81	z_5	*Direct*	-0.69	-1.73
	Indirect	0.55^{***}	5.72		*Indirect*	-0.70	-1.59
	Total	1.10^{***}	11.07		*Total*	-1.38	-1.68
x_1^2	*Direct*	0.10^{***}	6.10	z_6	*Direct*	-0.23	-0.97
	Indirect	0.10^{***}	4.23		*Indirect*	-0.23	-0.94
	Total	0.21^{***}	5.45		*Total*	-0.46	-0.96
x_2^2	*Direct*	0.03^{***}	3.45	z_7	*Direct*	-0.33	-1.22
	Indirect	0.03^{**}	3.07		*Indirect*	-0.33	-1.18
	Total	0.05^{***}	3.39		*Total*	-0.66	-1.21
x_1x_2	*Direct*	-0.09^{***}	-5.05	z_8	*Direct*	-0.08^{**}	-2.78
	Indirect	-0.09^{***}	-3.93		*Indirect*	-0.08^{*}	-2.33
	Total	-0.18^{***}	-4.75		*Total*	-0.17^{**}	-2.60
t	*Direct*	-0.03^{***}	-12.95	z_9	*Direct*	0.02	0.56
	Indirect	-0.04^{***}	-4.37		*Indirect*	0.02	0.56
	Total	-0.07^{***}	-6.79		*Total*	0.04	0.56
z_1	*Direct*	0.48	1.25	z_{10}	*Direct*	0.64^{***}	10.41
	Indirect	0.49	1.17		*Indirect*	0.65^{***}	4.66
	Total	0.97	1.21		*Total*	1.29^{***}	7.16
z_2	*Direct*	0.08	0.86	z_{11}	*Direct*	1.28^{***}	6.67
	Indirect	0.08	0.82		*Indirect*	1.28^{***}	4.15
	Total	0.15	0.84		*Total*	2.56^{***}	5.56
z_3	*Direct*	-0.02	-0.40				
	Indirect	-0.02	-0.38				
	Total	-0.04	-0.39				

SARPF denotes spatial autoregressive stochastic production frontier model.
*, ** and *** denote statistical significance at the 5%, 1% and 0.1% levels, respectively.

Table 6: Own efficiencies from the preferred spatial Durbin frontier and non-spatial and spatial autoregressive frontiers

	NSPF			SARPF W_{All}^{Row}			SDPF W_{All}^{Row}		
Country	Own VE	Own IE	Own CE	Own VE	Own IE	Own CE	Own VE	Own IE	Own CE
AGO	0.876 (37)	0.774 (36)	0.678 (37)	0.872 (38)	0.602 (36)	0.525 (36)	0.874 (35)	0.640 (35)	0.559 (35)
BDI	0.882 (8)	0.795 (30)	0.701 (29)	0.879 (12)	0.668 (27)	0.587 (27)	0.879 (18)	0.687 (30)	0.604 (30)
BEN	0.877 (35)	0.816 (19)	0.716 (20)	0.875 (30)	0.708 (22)	0.619 (22)	0.876 (26)	0.727 (26)	0.637 (26)
BFA	0.882 (11)	0.791 (31)	0.698 (30)	0.878 (16)	0.641 (34)	0.563 (34)	0.879 (19)	0.690 (29)	0.607 (29)
BWA	0.882 (14)	0.859 (5)	0.758 (4)	0.878 (15)	0.805 (9)	0.707 (8)	0.879 (20)	0.804 (10)	0.707 (9)
CAF	0.881 (17)	0.761 (40)	0.671 (40)	0.877 (22)	0.521 (41)	0.457 (40)	0.878 (22)	0.599 (41)	0.526 (40)
CIV	0.882 (7)	0.808 (22)	0.713 (21)	0.879 (8)	0.709 (21)	0.624 (21)	0.880 (7)	0.738 (21)	0.650 (20)
CMR	0.880 (24)	0.809 (21)	0.712 (22)	0.876 (24)	0.701 (24)	0.614 (24)	0.877 (25)	0.727 (25)	0.638 (25)
COD	0.867 (43)	0.625 (47)	0.542 (47)	0.861 (43)	0.299 (47)	0.257 (47)	0.862 (44)	0.340 (47)	0.293 (47)
COG	0.869 (42)	0.801 (27)	0.696 (31)	0.864 (42)	0.661 (30)	0.571 (33)	0.866 (41)	0.674 (32)	0.583 (33)
CPV	0.879 (30)	0.779 (34)	0.685 (35)	0.875 (28)	0.655 (33)	0.573 (31)	0.876 (28)	0.646 (34)	0.565 (34)
DJI	0.881 (22)	0.838 (12)	0.738 (11)	0.877 (23)	0.703 (23)	0.617 (23)	0.879 (16)	0.764 (16)	0.671 (16)
EGY	0.879 (29)	0.837 (14)	0.736 (13)	0.874 (32)	0.758 (18)	0.663 (18)	0.873 (36)	0.784 (15)	0.684 (15)
ETH	0.877 (36)	0.742 (42)	0.651 (41)	0.872 (36)	0.504 (43)	0.440 (43)	0.874 (34)	0.543 (43)	0.475 (43)
GAB	0.880 (27)	0.815 (20)	0.717 (19)	0.875 (29)	0.766 (17)	0.670 (17)	0.876 (29)	0.740 (20)	0.648 (21)
GHA	0.880 (26)	0.771 (38)	0.678 (36)	0.876 (27)	0.605 (35)	0.530 (35)	0.876 (27)	0.621 (37)	0.544 (37)
GIN	0.882 (10)	0.825 (17)	0.727 (16)	0.879 (5)	0.779 (15)	0.685 (14)	0.879 (15)	0.792 (13)	0.697 (13)
GMB	0.882 (4)	0.855 (8)	0.754 (6)	0.880 (1)	0.821 (6)	0.722 (4)	0.881 (5)	0.832 (4)	0.733 (4)
GNB	0.882 (6)	0.779 (35)	0.687 (33)	0.879 (10)	0.662 (28)	0.582 (28)	0.879 (14)	0.666 (33)	0.586 (32)
GNQ	0.862 (44)	0.856 (6)	0.738 (12)	0.860 (44)	0.832 (4)	0.716 (6)	0.863 (43)	0.820 (6)	0.708 (8)
KEN	0.883 (3)	0.817 (18)	0.721 (18)	0.879 (7)	0.685 (26)	0.602 (26)	0.881 (3)	0.741 (18)	0.653 (17)
LBR	0.861 (46)	0.745 (41)	0.641 (44)	0.856 (46)	0.525 (40)	0.449 (41)	0.857 (46)	0.609 (40)	0.522 (41)
LSO	0.881 (18)	0.844 (11)	0.744 (9)	0.878 (19)	0.778 (16)	0.683 (15)	0.880 (12)	0.794 (12)	0.699 (12)
MAR	0.881 (21)	0.797 (29)	0.702 (28)	0.879 (13)	0.717 (19)	0.630 (19)	0.881 (6)	0.735 (23)	0.647 (23)
MDG	0.878 (32)	0.783 (33)	0.687 (34)	0.872 (35)	0.573 (37)	0.500 (37)	0.874 (33)	0.617 (39)	0.540 (39)
MLI	0.882 (13)	0.807 (23)	0.712 (23)	0.878 (14)	0.698 (25)	0.613 (25)	0.880 (13)	0.742 (17)	0.653 (18)
MOZ	0.880 (25)	0.737 (43)	0.648 (42)	0.876 (25)	0.453 (44)	0.397 (44)	0.878 (23)	0.508 (44)	0.446 (44)
MRT	0.882 (9)	0.805 (25)	0.710 (24)	0.879 (9)	0.710 (20	0.624 (20)	0.880 (8)	0.735 (22)	0.647 (22)
MUS	0.882 (15)	0.867 (3)	0.764 (3)	0.879 (11)	0.843 (3)	0.741 (3)	0.880 (10)	0.849 (3)	0.747 (3)
MWI	0.882 (16)	0.767 (39)	0.676 (38)	0.878 (20)	0.550 (39)	0.483 (38)	0.880 (11)	0.635 (36)	0.558 (36)
NAM	0.882 (5)	0.855 (7)	0.754 (5)	0.880 (2)	0.813 (7)	0.715 (7)	0.880 (9)	0.815 (9)	0.717 (5)
NER	0.882 (12)	0.735 (44)	0.648 (43)	0.878 (17)	0.506 (42)	0.444 (42)	0.879 (17)	0.579 (42)	0.509 (42)
NGA	0.851 (47)	0.668 (46)	0.569 (46)	0.846 (47)	0.404 (46)	0.342 (46)	0.846 (47)	0.428 (46)	0.362 (46)
RWA	0.875 (38)	0.830 (16)	0.726 (17)	0.872 (37)	0.781 (14)	0.681 (16)	0.873 (37)	0.788 (14)	0.688 (14)
SDN	0.883 (2)	0.883 (2)	0.779 (2)	0.880 (3)	0.859 (2)	0.755 (2)	0.881 (4)	0.873 (2)	0.769 (1)
SEN	0.880 (23)	0.806 (24)	0.709 (25)	0.878 (21)	0.802 (10)	0.704 (9)	0.874 (32)	0.711 (27)	0.622 (27)
SLE	0.862 (45)	0.846 (10)	0.729 (15)	0.859 (45)	0.812 (8)	0.698 (10)	0.860 (45)	0.818 (8)	0.703 (11)
STP	0.879 (28)	0.787 (32)	0.692 (32)	0.876 (26)	0.657 (31)	0.576 (30)	0.877 (24)	0.680 (31)	0.597 (31)
SWZ	0.871 (40)	0.863 (4)	0.752 (7)	0.869 (40)	0.828 (5)	0.720 (5)	0.870 (40)	0.824 (5)	0.717 (6)
TCD	0.878 (31)	0.850 (9)	0.746 (8)	0.874 (31)	0.788 (12)	0.690 (13)	0.875 (31)	0.818 (7)	0.716 (7)
TGO	0.881 (20)	0.802 (26)	0.706 (26)	0.878 (18)	0.661 (29)	0.580 (29)	0.878 (21)	0.735 (24)	0.645 (24)
TUN	0.881 (19)	0.838 (13)	0.738 (10)	0.879 (6)	0.785 (13)	0.690 (12)	0.881 (2)	0.802 (11)	0.707 (10)
TZA	0.878 (33)	0.706 (45)	0.619 (45)	0.873 (33)	0.418 (45)	0.365 (45)	0.875 (30)	0.496 (45)	0.435 (45)
UGA	0.878 (34)	0.801 (28)	0.703 (27)	0.873 (34)	0.655 (32)	0.572 (32)	0.873 (38)	0.698 (28)	0.609 (28)
ZAF	0.883 (1)	0.832 (15)	0.734 (14)	0.880 (4)	0.792 (11)	0.697 (11)	0.881 (1)	0.740 (19)	0.652 (19)
ZMB	0.874 (39)	0.772 (37)	0.675 (39)	0.869 (39)	0.554 (38)	0.482 (39)	0.872 (39)	0.620 (38)	0.540 (38)
ZWE	0.869 (41)	0.897 (1)	0.780 (1)	0.866 (41)	0.890 (1)	0.770 (1)	0.866 (42)	0.887 (1)	0.767 (2)
Sample Average	0.877	0.802	0.703	0.874	0.679	0.594	0.875	0.704	0.617

NSPF - non-spatial stochastic production frontier; SARPF - spatial autoregressive stochastic production frontier; SDPF - spatial Durbin stochastic production frontier. IE, VE and CE - time-invariant, time-variant and combined time-variant efficiencies, respectively. Efficiency rankings are in descending order and are in parentheses.
AGO - Angola; BDI - Burundi; BEN - Benin; BFA - Burkina Faso; BWA - Botswana; CAF - Central African Republic; CIV - Côte d'Ivoire; CMR - Cameroon; COD - Democratic Republic of the Congo; COG - Congo; CPV - Cape Verde; DJI - Djibouti; EGY - Egypt; ETH - Ethiopia; GAB - Gabon; GHA - Ghana; GIN - Guinea; GMB - The Gambia; GNB - Guinea-Bissau; GNQ - Equatorial Guinea; KEN - Kenya; LBR - Liberia; LSO - Lesotho; MAR - Morocco; MDG - Madagascar; MLI - Mali; MOZ - Mozambique; MRT - Mauritania; MUS - Mauritius; MWI - Malawi; NAM - Namibia; NER - Niger; NGA - Nigeria; RWA - Rwanda; SDN - Sudan; SEN - Senegal; SLE - Sierra Leone; STP - Sao Tome and Principe; SWZ - Swaziland; TCD - Chad; TGO - Togo; TUN - Tunisia; TZA - United Republic of Tanzania: Mainland; UGA - Uganda; ZAF - South Africa; ZMB - Zambia; ZWE - Zimbabwe.

Table 7: Selected average direct, indirect and total combined technical efficiency scores and rankings from the preferred spatial Durbin frontier

Ranking	Country	Av CE^{Dir} Score	Country	Av CE^{Ind}_{Imp} Score	Country	Av CE^{Ind}_{Exp} Score	Country	Av CE^{Tot}_{Imp} Score	Country	Av CE^{Tot}_{Exp} Score
1	Zimbabwe	0.772	Guinea-Bissau	0.310	The Gambia	0.517	Sudan	1.069	The Gambia	1.270
2	Sudan	0.771	Cape Verde	0.307	Togo	0.436	Zimbabwe	1.067	Zimbabwe	1.153
3	The Gambia	0.753	Liberia	0.307	Rwanda	0.436	Mauritius	1.047	Equatorial Guinea	1.146
4	Mauritius	0.748	South Africa	0.307	Senegal	0.434	The Gambia	1.041	Rwanda	1.131
5	Swaziland	0.721	Senegal	0.306	Equatorial Guinea	0.433	Swaziland	1.023	Guinea	1.100
47	DR Congo	0.294	Rwanda	0.288	DR Congo	0.152	DR Congo	0.596	DR Congo	0.446
46	Nigeria	0.364	The Gambia	0.289	Cape Verde	0.168	Nigeria	0.668	Nigeria	0.568
45	Tanzania	0.437	Togo	0.293	Madagascar	0.183	Tanzania	0.736	Tanzania	0.647
44	Mozambique	0.448	Equatorial Guinea	0.293	Mauritius	0.185	Mozambique	0.751	Mozambique	0.651
43	Ethiopia	0.477	Malawi	0.294	Tunisia	0.195	Ethiopia	0.781	Ethiopia	0.678
	Sample	0.621	Sample	0.300	Sample	0.300	Sample	0.921	Sample	0.921

CE denotes combined time-variant technical efficiency; Dir, Ind and Tot denote direct, indirect and total, respectively; and Imp and Exp denote efficiency imports and exports, respectively. Efficiency rankings are in descending order.