Real convergence using TAR panel unit root tests: an application to Southern African Development Community

Christian Kakese Tipoy

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Abstract

The recent European Union crisis has sparked renewed interest in the achievement of convergence among potential member states prior to the establishment of a monetary union. This article examines real convergence in the per capita output of SADC countries using annual data from 1980 to 2013. An extension of the Evans & Karras' approach that combines threshold modelling, panel data unit root testing and critical values bootstrapping is used in order to test for convergence. We find that the TAR specification outperforms the linear specification while testing convergence among the SADC richer countries and the SADC community as a whole. While considering the SADC middle income countries, the CMA and SACU regions; the linear performs better. Strong significant convergence is found only for SADC richer countries and the SACU union while the middle countries are characterized by a weak convergence. For the SADC community as a whole and the CMA region, there is significant divergence. These findings cast doubt on the establishment of an efficient monetary union among SADC' member states in the short run.

Keywords: real convergence, panel data unit root test, bootstrap, threshold model, SADC.

JEL Classification: C12, C33, F43

1 Introduction

One of the goals of the African Union (AU) is to create a monetary union in stages for the entire continent starting with each of the different sub-regions (Masson & Patillo 2005). Building from that, the Southern African Development Community (SADC)[1] has embarked on a project of establishing a mon-

*Lecturer. School of Accounting, Economics and Finance. University of KwaZulu-Natal, Durban 4041, South Africa. Ph +27 31 260 7870. E-mail: dchristipoy@gmail.com / tipoy@ukzn.ac.za

[1]SADC comprises Angola, Botswana, Democratic Republic of Congo, Malawi, Namibia, Lesotho, Madagascar, Mauritius, Mozambique, Seychelles, Swaziland, South Africa, Tanzania, Zambia and Zimbabwe.

etary union by 2016 and a single central bank and a single currency by 2018. The community has agreed on a set of macroeconomic criteria that will allow monitoring of progress towards convergence (Bala 2011).

According to Solow (1956) and subsequent literature, economic integration, under free factor mobility and international diffusion of technological knowledge, will automatically promote economic convergence. However, a different view is that integration will increase regional and geographical disparities as the factors of production will be concentrated in the more developed regions as a result of increasing returns to scale and externalities (Krugman 1990; Romer 1986; Romer 1990).

A fast and automatic economic convergence allows free market forces to erode regional inequalities inhibiting transfer from the richer members' economies to the poorer of the economic union. However, if this convergence does not take place or is not sufficiently rapid, there is a need of an explicit regional policy in favour of the less developed economies of the union as long as this allows a reduction of inequalities (Beyaert 2003).

Since the seminal paper of Mundell (1961); McKinnon (1963); Kennen (1969) and Ingram (1973), a sizable literature exists that analyses the conformity of countries to the optimum currency area (OCA) criteria. For the SADC region, we can note the different contributions, among others, of Jefferis (2007), Kumo (2011), Breitenbach *et al.* (2012) and Zerihun *et al.* (2014). Looking at convergence, the concept involved traditionally an analysis of whether the real per capita incomes of poor countries were catching up with those of the rich countries. Since recent decades, there was a shift from that traditional view as regional economic integration required the strengthening of macroeconomic policies (Kumo 2011). De Haan *et al.* (2008) emphasize the importance of symmetric business cycles among countries forming a monetary union. This is crucial as considerable divergence will imply a non-optimal common monetary policy for all the member states. Furthermore, the recent Greek crisis, which threatened the whole Euro zone, showed the importance of a proper assessment of potential candidates for a monetary union.

The aim of this article is to assess convergence in SADC real per capita output[2]. A reason for analysing co-movements in real output is that countries facing high correlations of cyclical movements of real output do not need country specific monetary and exchange rate policies (Tavlas 2008) and can therefore be successful in forming a currency union.

The article uses a non-linear bootstrap extension of the Evans & Karras (1996a) approach. As explained by Beyaert & Camacho (2008), there is a belief that the convergence process is not uniform as countries may only converge once certain institutional economic and political conditions are put in place. Another possibility is that convergence may take place at a specific rate under certain conditions and at another rate under other conditions; justifying the use of a non-linear technique.

[2] Convergence test can also be conducted using exchange rates. However, we are interested only in real GDP in this article.

We find that the threshold autoregressive (TAR) specification outperforms the linear specification while testing convergence among the SADC richer countries and the SADC community as a whole. While considering the SADC middle income countries, the CMA and the SACU regions; the linear performs better. Strong significant convergence is found only for SADC richer countries and the SACU union while the middle countries are characterized by weak convergence. For the SADC community as a whole and the CMA region, there is significant divergence. These findings cast doubt on the establishment of an efficient monetary union among SADC' member states in the short run.

The rest of the paper is organized as follows. Section 2 looks at a brief literature review focused on convergence in Africa with a particular focus in the SADC region. Section 3 explains the Evans & Karras (1996a) linear framework. Section 4 describes the TAR extension of the Evans & Karras' (1996a) method. Section 5 uses both these methods to test for convergence in the per capita output of SADC countries from 1980 to 2013. Section 6 concludes.

2 A brief literature review

There are two concepts of convergence in the literature. The first concept explains convergence as a catching up process in gross national product per capita in order to achieve an alignment of the standards of living in the different participant states of a monetary union (Wagner 2013). Barro & Sala-i-Martin (2004) have demonstrated that countries having lower starting values of capital-labor ratio have higher per capita growth rates and tend to catch up with those having higher capital-labor ratios. Thus, countries are said to converge if the poorer country with lower initial income grows faster than others (Kumo 2011). This is the beta (β) convergence concept.

The second concept looks at cross-sectional dispersion. Convergence will therefore occur if the dispersion, proxied for example by the standard deviation of the logarithm of per capita income across a group of countries, declines over time. This is the sigma (σ) convergence concept. Although β-convergence tends to generate σ-convergence, Barro & Sala-i-Martin (2004) have shown that β-convergence is a necessary but not a sufficient condition for σ-convergence.

There will be absolute convergence whenever per-capita incomes of countries converge to a unique steady state value, implying an equalization of incomes between the countries. Conditional convergence, on the contrary, implies different steady states to which per capita incomes of countries converge. According to Varblane &Vahter (2005), absolute convergence will occur in countries with similar initial levels of income and similar economic, political and social structures; leading to σ-convergence or club-convergence.

The conventional approach of testing convergence estimates, for a sample of countries, cross-sectional relationship between the growth rate of output per capita and the initial level of output over some period; with the possibility of controlling for other variables (Evans & Karras 1996b). Evans (1995) shows that this approach produces valid inference under unrealistic conditions:

the dynamic structures of the different countries should have identical first order autoregressive representations; every economy affects every other economy completely symmetrically; and the vector of variables control for all permanent cross-economy differences. Evans & Karras (1996a) and Evans (1998) propose the use of a panel data approach.

Using unit root and cointegration tests for panel data, McCoskey (2002) investigates the convergence properties of six well-being indicators in Sub-Saharan Africa namely government share of GDP, capital per worker, openness of the economy, real GDP per capita, standard of living and real GDP per worker from 1960 to 1990. The countries were divided into clubs and the author has also investigated convergence among Southern African Custom Union (SACU) and SADC countries. Little evidence of long-run relationship was found for income based variables, except for real GDP per capita and for some sub-club such as the one comprising South Africa and Malawi. Using unit root tests, no evidence of convergence was found for real GDP based variables; nor for government share of GDP and real GDP based variables for SACU and SADC countries.

Kumo (2011) has used the concept of β and σ convergence to analyse real GDP absolute and conditional convergence in SADC countries for the period 1992-2009. No convergence was found for the SADC as a whole, nor for the Common Monetary Area (CMA) countries comprising South Africa, Lesotho, Namibia and Swaziland. However, while considering individual countries, convergence towards common stochastic trends was found for South Africa and Botswana.

3 Review of the linear framework[3]

3.1 The basic Evans-Karras procedure

Evans & Karras (1996a) test real convergence in a panel data using the following specification:

$$\Delta g_{n,t} = \delta_n + \rho_n, g_{n,t-1} + \sum\nolimits_{i=1}^{p} \varphi_{n,i} \Delta g_{n,t-i} + \varepsilon_{n,t} \tag{1}$$

with $n = 1, ...N$ and $t = 1..., T$. The subscript n refers to cross-sectional unit and t refers to time period. The variable $g_{n,t}$ is defined as:

$$g_{n,t} = y_{n,t} - \bar{y}_t; \tag{2}$$

where $y_{n,t} = \log(Y_{n,t})$, with $Y_{n,t}$ being the per-capita income of country n in real terms and $\bar{y}_t = \frac{1}{N} \sum_{n=1}^{N} y_{n,t}$ being the cross-country average log of per-capita income at time t.

A $\rho_n = 0$ implies that the N countries diverge, whereas $0 < -\rho_n < 1$ for all n is a convergence condition. Beyaert (2005) has shown that divergence of one single country in the panel implies that the $g_{n,t}$ will be $I(1)$ for all n. The

[3] An adaptation of Beyaert & Camacho (2008). Refer to the article for full description.

convergence will be absolute if $\delta_n = 0$ for all n whereas it will be conditional if not.

Evans & Karras (1996a) apply Ordinary Least Squares (OLS) to (1) in order to obtain an estimate of the standard deviation of ε_n, say s_n; and use it to transform the data to $w_{n,t} = g_{n,t}/s_n$. Then obtain the OLS estimate of ρ and its t-ratio applying OLS to the equation:

$$\Delta w_{n,t} = \delta_n + \rho w_{n,t-1} + \sum\nolimits_{i=1}^{p} \varphi_{n,i} \Delta w_{n,t-i} + \varepsilon_{n,t} \tag{3}$$

If this t-ratio is sufficiently negative, reject the null in the test:

$$\rho_n = 0 \forall n \; against \; \rho_n < 0 \forall n \tag{4}$$

Under the alternative, the economies converge. Otherwise, they diverge. This is just testing that the series of the panel exhibit a unit root. If divergence is rejected in the third step, test the null that:

$$\delta_n = 0 \forall n \; against \; \delta_n \neq 0 \forall n \tag{5}$$

for some n in equation (1). For that purpose, estimate this equation for $n = 1, ..., N$; compute $\Phi = \frac{1}{N} \sum_{n=1}^{N} (t^2_{\hat{\delta}_n})$; and reject the null if Φ is too large, in which case convergence would be conditional. Otherwise, convergence is absolute.

If the errors in (1) are contemporaneously uncorrelated, Evans & Karras (1996a) show that the tests for hypothesis (4) and (5) will have asymptotic distributions whenever N and T tend to infinity. They suggest an improvement that use critical values derived through simulations from Normal independent distributions.

The limitations of this approach as identified by Beyaert & Camacho (2008) are twofold. First, the assumption of cross-sectional dependence is difficult to hold when having low to moderate income countries. Second, the assumption of linearity in (1) is unrealistic as some countries may have experienced profound institutional and economic changes during the period under study.

To address these limitations, Beyaert & Camacho (2008) have considered two simulations extensions of the Evans-Karras approach. The first one relaxes the assumption of cross-sectional independence building on Chang (2004) results on the use of bootstrap critical values in presence of cross sectional dependence. The second considers the fact that the dynamics of the convergence process may not be uniform overtime and change with institutional and economic circumstances of the countries, providing grounds for the use of a panel data TAR model.

3.2 A bootstrap version of Evans-Karras approach

Beyaert & Camacho[4] (2008) propose a bootstrap version of Evans-Karras' approach. In model (1), p is supposed to be high enough so that $\varepsilon_{n,t}$ is a white

[4] We are grateful to these authors for making the Gauss codes available.

noise process for each n and that errors are not serially correlated. However, cross-country contemporaneous correlations will still be present. Thus, convergent countries will tend to be affected by the same type of shocks.

They express (1) in a Seemingly Unrelated Regression Estimation (SURE) form as:

$$\Delta G = X\beta + \varepsilon, \tag{6}$$

where $X = (\breve{\imath}, \breve{G}_{-1}, \Delta\breve{G}_{-1}, ..., \Delta\breve{G}_{-p})$, with components:

$$\breve{\imath} = \begin{bmatrix} \bar{1}_T & & 0 \\ & \ddots & \\ 0 & & \bar{1}_T \end{bmatrix}, \ with\ \bar{1}_T = [1, ..., 1]'_{Tx1};$$

$$\breve{G}_{-1} = \begin{bmatrix} G_{1,-1} & & 0 \\ & \ddots & \\ 0 & & G_{N,-1} \end{bmatrix}, \ where\ G_{n,-1}\ is\ G_n\ lagged\ one\ period;\ similarly$$

$$\Delta\breve{G}_{-i} = \begin{bmatrix} \Delta G_{1,-1} & & 0 \\ & \ddots & \\ 0 & & \Delta G_{N,-i1} \end{bmatrix}, \ for\ i = 1, ..., p\ where\ \Delta G_{n,-i}\ is\ \Delta G_n\ lagged\ i\ periods.$$

Model (6) can be estimated by OLS and an estimate $\hat{} = [s_{nm}]$ can be computed, with $s_{nm} = \frac{1}{T}\sum_{t=1}^{T} e_{nt}e_{mt}$ for $n, m = 1, ..., N$; where e_{it} is the OLS residual of model (6) corresponding to observation t for country l. The Feasible Generalised Least Squares (FGLS) estimator of β is then:

$$\hat{\beta}_{FGLS} = [X'\hat{V}^{-1}X]^{-1}X'\hat{V}^{-1}\Delta G; \tag{7}$$

where $\hat{V} = \quad I_T$.

The hypothesis of divergence against convergence as described by (4) is tested by estimating model (6) using FGLS under the restriction that $\rho_n = \rho$ for all n and computing the t-statistic associated with the estimation of the restricted coefficient computed. The p-value is obtained by bootstrap. For that purpose, an FGLS estimate of model (1) is obtained under the additional restriction that $\rho = 0$, with the residuals recentered and arranged in a matrix[5], then resampled with replacement in order to obtain a new time series of residuals for each n that preserves the initial contemporaneous correlation among the series (Maddala & Wu 1999; Chang 2004). Bootstrap data are then generated back from these resampled residuals using the FGLS coefficient estimates of model (1) under $\rho = 0$. The resampling and data generation process is repeated a very large number of times. The value of the test statistic is computed in each replication in the same way as on the observed data. The bootstrap p-value is the percentage of bootstrapped t-statistics falling to the left of the observed t-statistic.

[5] For each country n, the sample mean over time is subtracted from the residuals to obtain zero-mean residuals.

The bootstrapped version of test (5) is carried out in a similar way. Model (1) is estimated in SURE form by unrestricted FGLS. The following test-statistic is then computed:

$$\Phi = \frac{1}{N-1}\{\sum_{n=1}^{N}\left[t(\hat{\delta}_{FGLS,n})\right]^2\}, \tag{8}$$

where $\hat{\delta}_{FGLS,n}$ is the FGLS estimate of $\hat{\delta}_n$ in (6). Then, (6) is estimated under the restriction that $\delta_n = 0$ for all n, and the residuals are recentered and resampled by row. The bootstrap data are generated from these bootstrap residuals under this restriction and the corresponding bootstrap Φ statistics are computed. The bootstrap p-value for (8) is obtained from the relative position of observed Φ statistic in empirical distribution of the bootstrapped Φ statistics.

4 Convergence analysis with TAR models[6]

4.1 The non-linear model

Suppose that the convergence process is not uniform. It could be that the N countries converge only if certain institutional, political or economic conditions are fulfilled whereas they diverge otherwise. In this case, it may happen that $0 < -\rho_n < 1$ for all n under certain circumstances but that $\rho_n = 0$ if these circumstances are not met. Another possibility would be that convergence takes place at one rate in certain conditions and another rate under other conditions. That is, it may happen that $0 < -\rho_n < 1$ for all n but that its specific value differs according to the prevailing conditions at time t. A model that represents such behaviour can be specified as follows:

$$\begin{aligned}\Delta g_{n,t} = &[\delta_n^I + \rho_n^I, g_{n,t-1} + \sum_{i=1}^{p}\varphi_{n,i}^I \Delta g_{n,t-i}]I_{\{z_{t-1}<\lambda\}} \\ &+[\delta_n^{II} + \rho_n^{II}, g_{n,t-1} + \sum_{i=1}^{p}\varphi_{n,i}^{II} \Delta g_{n,t-i}]I_{\{z_{t-1}\geq\lambda\}} + \varepsilon_{n,t}\end{aligned} \tag{9}$$

with n =1,..., N; and t =1,...,T. In this model, $I\{x\}$ is an indicator which takes the value of 1 when x is true and zero otherwise. It acts as a dummy variable which takes a unit value if the condition $z_{t-1} < \lambda$ is fulfilled. So when $z_{t-1} < \lambda$, the model is $\Delta g_{n,t} = \delta_n^I + \rho_n^I, g_{n,t-1} + \sum_{i=1}^{p}\varphi_{n,i}^I \Delta g_{n,t-i} + \varepsilon_{n,t}$, whereas it is $\Delta g_{n,t} = \delta_n^{II} + \rho_n^{II}, g_{n,t-1} + \sum_{i=1}^{p}\varphi_{n,i}^{II} \Delta g_{n,t-i}]I_{\{z_{t-1}<\lambda\}} + \varepsilon_{n,t}$ when $z_{t-1} \geq \lambda$. So, at any t, the dynamics of the per capita incomes follows one of two possible regimes. We will call "regime I" the case where $z_{t-1} < \lambda$ and "regime II" the case where $z_{t-1} \geq \lambda$. The parameter λ is a "threshold" parameter and equation (9) belongs to the class of TAR models first introduced by Tong (1978). Model (9) includes the linear model (1) as a particular case, which takes place when z_{t-1} stands on the same side of λ for all t The threshold parameter is usually

[6] An adaptation of Beyaert and Camacho (2008). Refer to the article for full description.

unknown. In order to carry out the estimation process, the restriction that $0 < \pi_1 \leq P(z_{t-1} \leq \lambda) \leq 1 - \pi_1$ is imposed so that no regime takes place in less than a π_1 fraction of the total sample, with π_1 typically around 0.10 or 0.15. If π_1 falls below this limit, the linear process is preferred.

Compared to the Tong (1978) model, Beyaert & Camacho (2008) propose extensions in two directions. The first consists of abandoning the single equation time-series TAR model in favour of a multivariate panel data model. The second refers to the possible non-stationarity of the data, in the form of a unit root in the individual series when $\rho_n = 0$. The second extension has been considered by Caner & Hansen (2001) although their model is limited to a single series, whereas Beyaert & Camacho (2008) consider a panel of N time series.

Divergence will occur in model (9) if $\rho_n^I = \rho_n^{II} = 0$ for all n. Alternatively, global convergence would correspond to $0 < -\rho_n^i < 1$ for all n and $i = I, II$. Finally, there would be partial convergence if $0 < -\rho_n^i < 1$ but $\rho_n^j = 0$ for all n and $i \neq j$.

In (9), the so-called transition variable, z_t, can be either endogenous when its values are directly obtained from the $g_{n,t}$ variables; or exogenous, when it refers to an economic variable different from any $g_{n,t}$. In the endogeneity case, it makes sense to choose $z_t = g_{m,t} - g_{m,t-d}$, for some m and some $0 < d \leq p$; where m and d are not a priori fixed but rather determined endogenously.

In this way, from the statistical point of view, z_t, would be stationary, whether the economies converge ($g_{n,t}$ ~$I(0)$, for all n and both regimes) or not ($g_{n,t}$ ~$I(1)$,for one or both regimes). Economically, it means that the shift from one regime to another is related to the growth rate of country j in the last d periods. Another possibility would be to choose z_t exogenously, on the basis of economic arguments. For instance, the intensity of the convergence can be thought of as a process among the countries in the panel that varies given their degree of openness towards each other. Let op_t be some measure of intensity of international trade relations linking the countries of the panel. Then $z_t = op_{t-d}$ with d determined endogenously from the data or fixed exogenously. In this paper, d will be determined endogenously. The equation (9) also assumes that all the parameters change when the economies shift from regime I to regime II. However, restricted versions of this specification could be considered. For instance, the following specification

$$\Delta g_{n,t} = \delta_n[\rho_n^I, g_{n,t-1}]I_{\{z_{t-1}<\lambda\}} + [\rho_n^{II}, g_{n,t-1}]I_{\{z_{t-1}\geq\lambda\}} + \sum\nolimits_{i=1}^{p} \varphi_{n,i}\Delta g_{n,t-i} + \varepsilon_{n,t}, \tag{10}$$

with n =1,..., N; and t =1,..., T; assumes that only the convergence rate varies with this regime.

In (9) and (10), p is assumed to be high enough so that $\varepsilon_{n,t}$ is a white noise process for each n; excluding serial correlation in the errors. However, for the same reasons as in model (1), cross-country contemporaneous correlation cannot be excluded.

4.2 Estimation

Model (9) is estimated by least squares. However, given the dependence of the coefficients on the threshold value of the transition variable, both unknown; and given the structures of the variance-covariance matrix of the residuals, it is convenient to use concentration in a GLS approach.

Suppose that λ, m and d are known and their values are collected in vector $\theta_0 = (\lambda_0, m_0, d_0)'$. So, conditional on θ_0, model (9) can be seen as a panel data equation with known dummy variables. If the total number of available time observations for each country is $(T + p + 1)$ so that $(p + 1)$ initial values prior to $t = 1$ exist and $\odot$ denotes an element-by-element multiplication; (9) can be written in SURE form as:

$$\Delta G = [X \odot \breve{I}_{I,\theta_0} \vdots X \odot \tilde{I}_{II,\theta_0}] \begin{bmatrix} \beta_{I,\theta_0} \\ \cdots \\ \beta_{II,\theta_0} \end{bmatrix} + \varepsilon, \tag{11}$$

where $\beta_{I,\theta_0}(\beta_{II,\theta_0})$ is defined as a vector of parameter β in which the parameters of each country are stacked by type in a column They refer to the coefficients under regime I (II) when $\lambda = \lambda_0$, $m = m_0$ and $d = d_0$. The expression $\breve{I}_{I,\theta_0}$ refers to an $(NT$ x 1) vector obtained by stacking N times the $(T$ x 1) dummy variable vector.

$$I_{I,\theta_0} = [I_{z0,p<\lambda_0}, I_{z0,p+1<\lambda_0}, ..., I_{z0,T-1<\lambda_0}]'; \tag{12}$$

where $z_{0,t} = g_{m_0,t} - g_{m_0,t-d_0}$. Similarly, $\breve{I}_{II,\theta_0}$ is obtained by stacking N times the vector

$$I_{II,\theta_0} = [1 - I_{z0,p<\lambda_0}, 1 - I_{z0,p+1<\lambda_0}, ..., 1 - I_{z0,T-1<\lambda_0}]'; \tag{13}$$

Model (11) can be written more compactly as:

$$\Delta G = \breve{X}_{\theta_0}\beta_{\theta_0} + \varepsilon_t \tag{14}$$

Estimating this model by FGLS is justified by the characteristics of the variance-covariance matrix of the residuals. So:

$$\beta_{\theta,FGLS} = [\breve{X}'_{\theta_0} V_0^{-1} \breve{X}'_{\theta_0}]^{-1} \breve{X}'_{\theta_0} V_0^{-1} \Delta G; \tag{15}$$

where $\hat{V}_0 = \hat{}_0 \quad I_T$ and $\hat{}_0 = [s_{nm,0}]$ with $s_{nm,0} = \frac{1}{T}\sum_{t=1}^{T} e_{nt,0}e_{mt,0}$ for $n, m = 1, ..., N$; and with $e_{it,0}$ being the OLS residual of model (15) corresponding to observation t for country l

In practice, the true values of λ, m and d are unknown. However, we can infer appropriate values for these parameters from the data. Let us posit $\hat{e}_{\theta_0}$ the FGLS residual vector of model (11) and define the weighted sum of squared residuals $s^2_{\theta_0} = \frac{1}{T}\varepsilon'_{\theta_0}\hat{V}_0\hat{\varepsilon}_{\theta_0}$. Since this is a function of θ_0, a grid search procedure can be applied to obtain

$$\theta \equiv [\hat{\lambda}, \hat{m}, \hat{d}] = \arg \ \min_{\theta_0}(s^2_{\theta_0});$$

and the least squares estimates of the other parameters can be obtained by plugging in the point estimate $\hat{\theta}$ in model (11) and obtain the corresponding $\hat{\beta}_{\hat{\theta},FGLS}$.

The grid search procedure is implemented for each $m \epsilon [1, 2, ..., N]$ and each $d \epsilon [1, 2, ..., p]$ by giving to λ the value $(g_{m,\tau} - g_{m,\tau-d})$ for each $\tau \epsilon [1, 2, ..., T]$. The fraction of the sample falling in the implied regime I is then computed. If this fraction lies in the interval $[\pi_1, 1 - \pi_1]$, the corresponding FGLS estimator of β_0 and the weighted sum of residuals are computed. If not, this combination of m, d and λ is discarded and the procedure goes to the next point of the grid. Once all the points have been checked, the estimation process ends, obtaining θ and the corresponding $\hat{\beta}_{\hat{\theta},FGLS}$. This is the "grid-FGLS" method. Once model (9) is estimated, its superiority to the linear Evans-Karras method model (1) has to be checked. If confirmed, the next task will be to test if there is convergence or not by applying some type of unit-root test on the ρ coefficients of (9). If there is evidence of convergence, the last step should test absolute against conditional convergence through a test on the δ coefficients of (9).

4.3 The linearity test

The null hypothesis to be tested is that model (1) is correct, versus the alternative of model (9). The problem is that some parameters, namely λ, m and d; are not identified under the null since they are defined only under the alternative. As a consequence, conventional test statistics such as the likelihood ratio, Wald or LM tests; do not have standard distributions under this null. This problem has been pointed out by Hansen (1996) and examined for the single-equation multiple regime TAR model by Hansen (1999). Caner & Hansen (2001) also examined the problem when testing the single-equation two-regime TAR model with a unit-root. One of the best solutions proposed in the last two papers consists of obtaining the critical values by bootstrap simulations. An extension of this solution for the panel data TAR model (9) is described in what follows.

We want to test:

$$H_{0,1} : \delta_n^I = \delta_n^{II}, \rho_n^I = \rho_n^{II}, \varphi_{i,n}^I = \varphi_{i,n}^{II} \tag{16}$$

$\forall n = 1, ..., N$ and $\forall i = 1, ..., p$; against the alternative that not all the coefficients are equal in both regimes. For that purpose, estimate (1) by FGLS and (9) by the grid-FGLS method, then for each method, compute the value of the likelihood function of the estimation point and obtain:

$$\pounds_{1,2} = -2 \ln(L_1/L_2) \tag{17}$$

where L_1 is the likelihood value of one-regime linear model (1) and $L_{1,2}$ is the likelihood value of the two-regimes TAR model (9).[7] The null of linearity would be rejected if $\pounds_{1,2}$ is too large. In order to know how large $\pounds_{1,2}$ has to be,

[7] Alternatively, the weighted sum of squared residuals of each model could be computed and a Wald type test statistic could be built.

the critical values are obtained by mimicking Caner &Hansen's (2001) single equation procedure adapted to take into account the contemporaneous cross-country correlations of the errors As it is unknown whether the series exhibit unit root or not, two sets of bootstrap simulations should be conducted. The first is the unrestricted bootstrap simulation based on an unrestricted estimation of the linear model, as specified in (1). The second set is the restricted bootstrap which imposes a unit root by restricting $\rho_n = 0$ in (1). That is, the model considered under the null imposes both linearity and a unit root, as described by

$$\Delta g_{n,t} = \delta_n + \sum\nolimits_{i=1}^{p} \varphi_{n,i} \Delta g_{n,t-i} + \varepsilon_{n,t}, \tag{18}$$

with $n = 1, ..., N$ and $t = 1, ..., T$.

After simulations are carried out, if the linear model is rejected, the rest of the analysis is based on the TAR model (9).

4.4 Convergence tests

If model (9) is empirically favoured, the next step consists of testing convergence against divergence. The null hypothesis of the test is:

$$H_{0,2} : \rho_n^I = \rho_n^{II} = 0 \quad \forall n \tag{19}$$

If not rejected, it reflects that the countries diverge both under regime I and regime II. There are three types of alternatives of economic interest that can be tested:

$$H_{A,2a} : \rho_n^I < 0, \rho_n^{II} < 0 \quad \forall n \tag{20a}$$

$$H_{A,2b} : \rho_n^I < 0, \rho_n^{II} = 0 \quad \forall n \tag{20b}$$

$$H_{A,2c} : \rho_n^I = 0, \rho_n^{II} < 0 \quad \forall n \tag{20c}$$

The alternative (20a) reflects convergence of the countries both under regime I and II. This is the case of "full convergence". The alternatives (20b) and (20c) imply that convergence takes place only under regime I or only under regime II respectively. This is the case of "partial convergence."

Note that both the null and the alternative hypothesis are assuming that the coefficients satisfy the same property for all the countries at a time. This is consistent with the definition (2) of the series $g_{n,t}$. Since these series are in deviations from their common cross-section mean, as soon as one of the country does not converge to the other, even though the remaining countries do converge to each other; none of the $g_{n,t}$ series can be $I(0)$. In other words, the $g_{n,t}$ series of the panel are all $I(0)$ or all $I(1)$.

In order to discriminate between the three alternatives, several tests statistics are used along the lines of Caner & Hansen (2001) for the single-equation case. These authors propose a Wald-type statistics for the test against the global alternative H_{A2_a} of convergence. Extending their proposition to the panel-data case, the statistic is:

$$R_2 = t_I^2 + t_{II}^2, \tag{21}$$

Where t_I and t_{II} are t-type statistics associated with the estimation of ρ_n^I and ρ_n^{II}, respectively, in model (9). If $\hat{\rho}_n^I$ is the grid-GLS estimate of ρ_n^I for each regime i, we have:

$$t_1 = \frac{\hat{\rho}_n^I}{s_{p_n^i}}, \tag{22}$$

for $i = I, II$. Given the definition of R_2, large values of this statistic are favourable to convergence. For the alternative of partial convergence $H_{A,2b}$ the statistic to be used would be t_I while t_{II} would be used to test against the partial convergence hypothesis $H_{A,2c}$. These are left-sided tests. So, if $t_I(t_{II})$ is too small, whereas $t_{II}(t_I)$ is not, the data favour the hypothesis of convergence under regime I (II) and divergence under regime II (I). Bootstrap simulations are used in order to find the appropriate p-values. The statistics R_2, t_I and t_{II} are computed and sorted in ascending order to obtain the bootstrap p-values. The last step of the convergence analysis consists of discriminating between absolute and conditional convergence. The absolute convergence hypothesis refers to the fact that converging countries share the same steady path. Conditional convergence refers to the existence of parallel, though not coincident, paths. So, in terms of model (9), under the maintained hypothesis that $\rho_n^I < 0, \forall n = 1, ..., N$, and $i = I$, II; absolute convergence is equivalent to:

$$\delta_n^i = 0, \ \forall n = 1, ..., N, i = I, II \tag{23}$$

If the convergence process is partial, in the sense that it takes place only under one of the two regimes, say regime I, then absolute convergence would correspond to:

$$\delta_n^I = 0, \ \forall n = 1, ..., N \tag{24}$$

Note, however, that in this two-regime model, another case of interest occurs when $\rho_n^i < 0$ for all n and i (global convergence) but $\delta_n^i = 0$ for only one value of i. In this case, convergence is absolute under one regime although conditional under the other one. Several tests statistics are used to discriminate between these different cases. The proposed tests are based on the grid-GLS estimation of model (9). They are direct extensions to the TAR model of the statistics proposed by Evans & Karras (1996a) for the linear case and are derived from the t-statistics $t(\hat{\delta}_n^i) = \frac{\hat{\delta}_n^i}{s_{\hat{\delta}_n^i}}$, with $i = I$, II and $n = 1, ..., N$; associated with the estimated value of the constant terms. They are the following:

$$\Phi_a = \frac{1}{2N-1}\left\{\sum_{n=1}^{N}\left[t(\hat{\delta}_n^I)\right]^2 + \sum_{n=1}^{N}\left[t(\hat{\delta}_n^{II})\right]^2\right\} \tag{25a}$$

$$\Phi_b = \frac{1}{N-1}\left\{\sum_{n=1}^{N}\left[t(\hat{\delta}_n^I)\right]^2\right\} \tag{25b}$$

$$\Phi_c = \frac{1}{N-1}\left\{\sum_{n=1}^{N}\left[t(\hat{\delta}_n^{II})\right]^2\right\} \tag{25c}$$

Given the endogeneity of the transition variable, here too the bootstrap p-values are obtained from adjusting a linear model to the observed data. A null constant term is imposed in model (1) and the following specification is estimated:

$$\Delta g_{n,t} = \delta_n + \rho_n, g_{n,t-1} + \sum_{i=1}^{p} \varphi_{n,i} \Delta g_{n,t-i} + \varepsilon_{nt} \tag{26}$$

with $n = 1, ..., N$ and $t = 1, ..., T$ by feasible GLS. The matrix of recentered residuals is then resampled by row and the bootstrapped data are generated from the estimates of (26). Model (9) is adjusted on these data and the three tests Φ_a, Φ_b and Φ_c are computed. The bootstrap right-sided p-values are extracted from their empirical distributions. The three statistics are then used in the following way:

- If $H_{0,2}$ has been rejected in favour of $H_{A,2a}$:
  - Φ_a is too large: conditional convergence takes place under both regimes.
  - Φ_b is too large, although Φ_c is not: conditional convergence takes place under regime I and absolute convergence takes place under regime *II*.
  - Symmetrically Φ_c is too large, although Φ_b is not: conditional convergence takes place under regime II and absolute convergence takes place under regime I.
- If $H_{0,2}$ has been rejected in favour of $H_{A,2b}$:
  - Φ_b is too large: conditional convergence takes place under regime I.
  - Φ_b is not large enough: absolute convergence takes place under regime I.
- If $H_{0,2}$ has been rejected in favour of $H_{A,2c}$:
  - Φ_c is too large: conditional convergence takes place under regime *II*.
  - Φ_c is not large enough: absolute convergence takes place under regime *II*.

5 Empirical results

5.1 Data

The article uses annual data of logarithms of real per capita GDP of fifteen SADC countries from 1980 to 2013. The data were collected from the World Bank development indicators and are expressed in constant 2005 US dollars. The countries are divided into three sets The first set, called the richer or high income countries, comprises Botswana, Seychelles, Mauritius, South Africa and

Namibia. The second set, called the middle income countries, comprises Zambia, Swaziland, Angola and Lesotho. The last set, called the poorer or low income countries, comprises Zimbabwe, Tanzania, Mozambique, Madagascar, Malawi and the Democratic Republic of Congo. The countries were grouped under these sets given their average real GDP per capita. Besides SADC, the study analyses convergence among SACU and CMA countries. The former comprises South Africa, Namibia, Botswana, Swaziland and Lesotho while the latter comprises South Africa, Swaziland and Lesotho.

5.2 Results

To test for convergence, we follow the strategy used by Beyaert & Camacho (2008) as working with the deviation of per capita output from a common cross-country means that the divergence of one country implies that the whole set of $g_{n,t}$ series are $I(1)$. We start with the first set of richer countries for which convergence is highly probable. Once confirmed, we add countries to the set and repeat the convergence test on this augmented group. We carry on with the process until the last set comprises all the SADC countries. The data of the five richer countries are presented in figure 1. As it can be seen, there is a tendency of convergence between these countries as the gap between their outputs per capita becomes smaller over time It is therefore reasonable to expect convergence in the model following the different tests

Table 1 presents the results of the convergence tests for the first set of countries. The statistical results[8] are gathered in table 1.1 for the linear model (1) and in table 1.2 for the TAR model (9). The linear model shows strong convergence between countries. The convergence has been absolute during the whole period under study as the p-value of the test is equal to 0.200. However, while considering the TAR results, there is a strong rejection of the linear model in favour of the TAR model as both unrestricted and restricted p-values are 0.0070 and 0.0040 respectively. Thus, the process is better described by model (9). Botswana is the country whose evolution dictates the switch from one regime to the other. From figure 1, it can be seen that Botswana started at a lower position, together with Mauritius. The situation has since changed and Botswana ended up being among the top two richer countries in the last years of the sample. In that sense, Botswana is a good representative of the intensity of the convergence process; justifying its choice to form the transition variable. The estimate of the delay parameter d is 1 so that the transition variable is $g_{Botswana,t} - g_{Botswana,t-1}$. The threshold parameter λ is estimated at 5.47. This implies that regime I, which takes place in 83.87% of the sample, corresponds to the years in which the growth rate of Botswana's output per capita was 5.47 percentage points lower than the average growth rate of the set. By the same token, regime II, which takes place in 16.13% of the sample; corresponds to the years in which Botswana's growth rate was 5.47 percentage points higher. Given the p-values of 0.0010 and 0.0160 for regime I and II respectively, there

[8] All statistical tests are performed at the standard 5% critical value.

is convergence under both regimes leading to a full convergence. However, convergence under regime I seems to be stronger than convergence under regime II. The absolute versus conditional convergence test indicates that convergence was absolute under regime I and conditional under regime II.

Figure 2 identifies the periods that correspond to each regime, the threshold position and the value of the transition variable for the richer countries. Regime I dominated between 1985 and 1988 and during the last 20 years. Regime II took place during the early and late 80's. The five richer countries have converged towards a common steady state path during the last 20 years while, prior to that, they each converged towards their individual steady states. Therefore, the weighted average of their output per capita is economically meaningful and can be used as a benchmark in the analysis of convergence towards this first set. This is the next step.

We analyse the convergence of the middle income countries towards the average output per capita of the five richer. Figure 3 plots the growth rate of these countries and the average growth rates of the richer countries. These countries have slightly narrowed their distance with the five richer countries since the nineties. However, there is a slight divergence from 2003, explained probably by the larger increase in the growth rate of the richer countries.

Table 2.1 and 2.2 present the statistical results for this second set of countries. The linear portion indicates that there is convergence, although weak as it can be seen by the p-value of 0.0430. This convergence is absolute with the countries converging towards a unique steady state.The TAR model portion proves that linearity is not rejected given the p-values of 0.2370 for the unrestricted and 0.2220 for the restricted test. As the linear model outperforms the TAR, there is no need to do an interpretation of the latter. Therefore, there is absolute convergence during the whole period of analysis towards a unique steady state.

We extend the previous analysis with the inclusion of the third set of low income countries. From figure 4, we can note the large divergence in Zimbabwe's and D. R. Congo's outputs[9]. This divergence became more pronounced after the year 2005.Growth was, for most of the sample, sluggish for countries such as Malawi and Madagascar. Tanzania and Mozambique have displayed some convergence since the early nineties. However, there is a very weak tendency of narrowing the gap these past years for most of the countries. This may increase the probability of not rejecting divergence.

Looking at table 3.1, the linear model does not reject the hypothesis of divergence. However, the linear test on table 3.2 indicates that the TAR model outperforms the linear model. The country that dictates the transition from a regime to another is Angola. With an estimated d equals to 1 and a threshold value λ equals to 5.14, regime I, which takes place in 74.19% of the sample, corresponds to the period in which the growth rate of Angola was 5.14 percentage points lower than the average of the richer country. During this regime,

[9] Convergence tests were conducted without Zimbabwe and without Zimbabwe and D. R. Congo. Although the linear model outperformed the TAR model, no convergence was found for the remaining countries. The results are available upon request.

Angola grew much slower than the richer countries. Regime *II*, which occurs in 25.81% of the sample, corresponds to the period Angola's growth rate was 5.14 percentage points higher. From figure 4 we can note the rapid Angolan growth which started around 2002, explained by the end of the 26 years long civil war. Angola achieved astonishing growth and was ranked among the fastest growing economy in Southern Africa with growth of 15.7% in 2005 and 22.6% in 2006 (ECA 2007). This probably justifies its choice as the country that forms the threshold variable. The convergence test indicates that there is convergence during regime *II* and divergence during regime *I*. The convergence is absolute given the p-value of 0.3590. So under regime *II*, SADC countries converge to a unique steady state.

The periods when regime *II* prevails can be located looking at figure 5. Regime *II* coincides with the late eighties, the mid-nineties, the late nineties and the period between 2002 and 2003. This can be confirmed, looking at figure 4, as during these periods; Angola's output grew faster than that of other countries. As this absolute convergence has taken place only in 25.81 % of the sample, we can therefore conclude that there is a lack of convergence in the SADC region. This was even more pronounced during the past 10 years with significant divergence.

The last exercise was to test for convergence among CMA and SACU countries. This was done using South Africa's growth rate as the benchmark. This choice was justified by the fact that South Africa had the highest growth rate on average for the whole sample. So convergence for these sets means that they are catching up South Africa output per capita.

Table 4 presents the statistical results for CMA countries. The linear model outperforms the TAR model given the p-values of 0.1540 and 0.1580 for both unrestricted and restricted tests. The convergence test does not reject the null hypothesis of divergence. We can therefore conclude that Swaziland and Lesotho do not converge towards South Africa's.

Table 5 presents the results for the SACU countries. We just add Botswana and Namibia to the CMA group. The linear model slightly outperforms the TAR model. From the convergence test, we can note that there is strong convergence although conditional. Thus, SACU countries converge to their individual steady states. Convergence was probably found due to the larger impact of Botswana and Namibia on the test.

6 Conclusion

This article uses the Beyaert & Camacho non-linear extension of the Evans & Karras (1996a) approach to test real convergence in SADC annual real output per capita from 1980 to 2013. The methodology uses a threshold model, panel data unit root tests and bootstrap critical values in order to test for convergence.

The test was first conducted on a set of five rich or high income countries for which convergence is highly probable. This set comprises Botswana, Seychelles, Mauritius, South Africa and Namibia. The TAR model outperformed

the linear model and these richer countries were characterized by strong absolute convergence during the past 20 years.

The first set of richer countries was updated by adding a second set of middle income countries of the region. This new set comprises Zambia, Swaziland, Angola and Lesotho. We analyzed convergence of real output per capita of the countries of the second set towards the average output per capita of the five richer. Although the linear model outperformed the TAR model, we found a weak convergence towards a common steady state.

A last set of countries comprising Zimbabwe, Tanzania, Mozambique, Madagascar, Malawi and the Democratic Republic of Congo; was added to the two previous ones. The TAR model outperformed the linear model. However, few short periods of absolute convergence were found prior to 2003. During the past ten years there was a significant divergence of real output per capita of SADC countries as a whole.

The article also tested real convergence in the CMA which links South Africa, Lesotho and Swaziland in a monetary union; and SACU which consists of South Africa, Botswana, Namibia, Lesotho and Swaziland. There was a lack of significant convergence among the CMA countries. However the linear model, which slightly outperformed the TAR model, indicated a strong conditional convergence among the SACU countries. This may be explained by the richer countries of the union such as Botswana and Namibia.

Given these findings, the SADC community, as a whole, does not conform to the OCA criteria. The recent Euro zone crisis has reinforced the need of convergence prior to the establishment of a monetary union. SADC needs to reinforce and monitor the progress of member states towards the achievement of macroeconomic targets as agreed. Only when convergence is achieved then the establishment of a monetary union can follow with far less risks of destabilisation through exogenous shocks.

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Figure 1 Output evolution of the five richer countries (in logs)

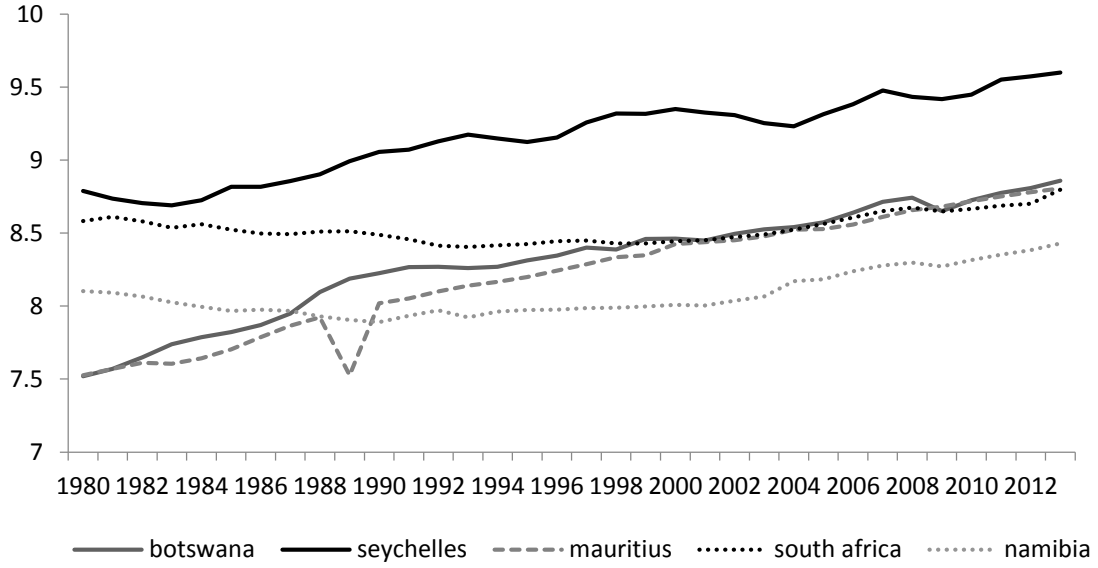

Figure 2 Threshold variable for the fiver richer countries

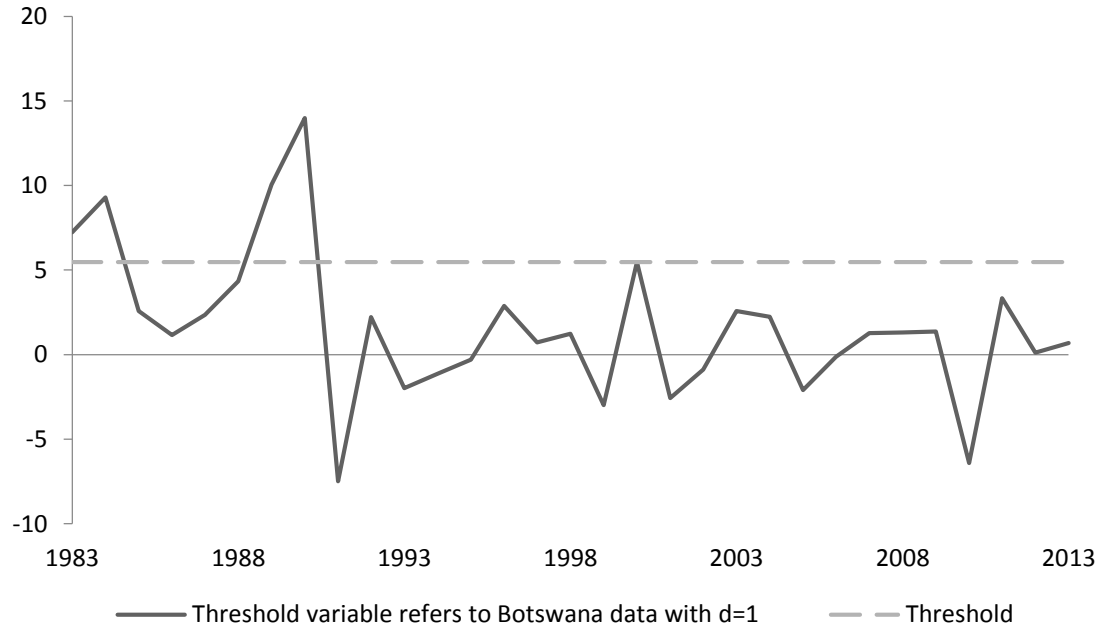

Figure 3 Output evolution of average of the five richer and the middle countries

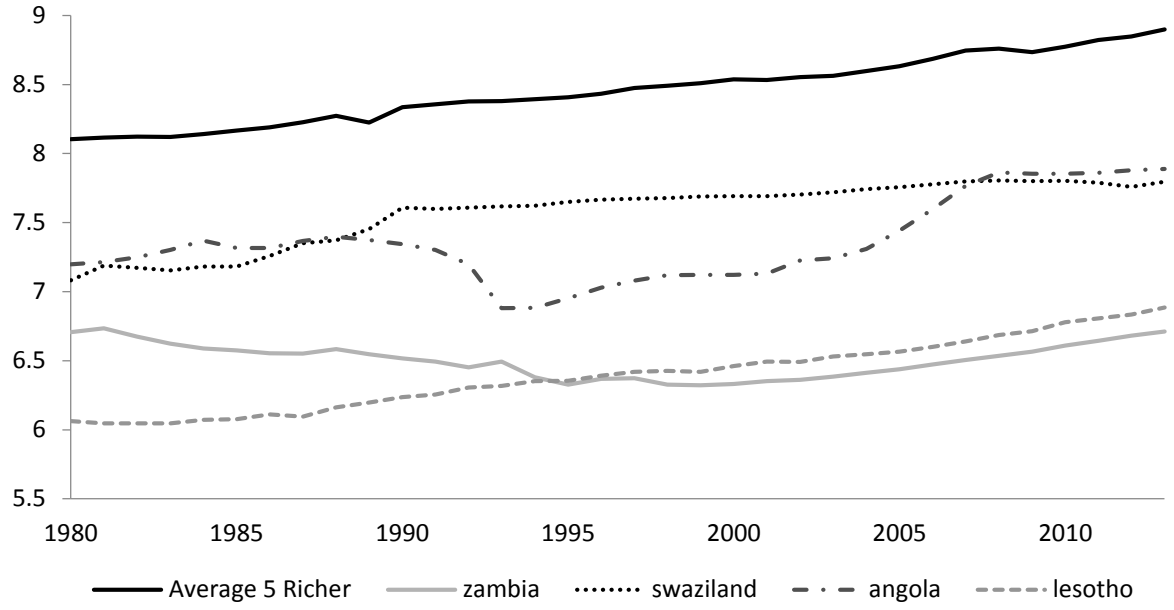

Figure 4 Output evolution of average of the five richer and other SADC counties

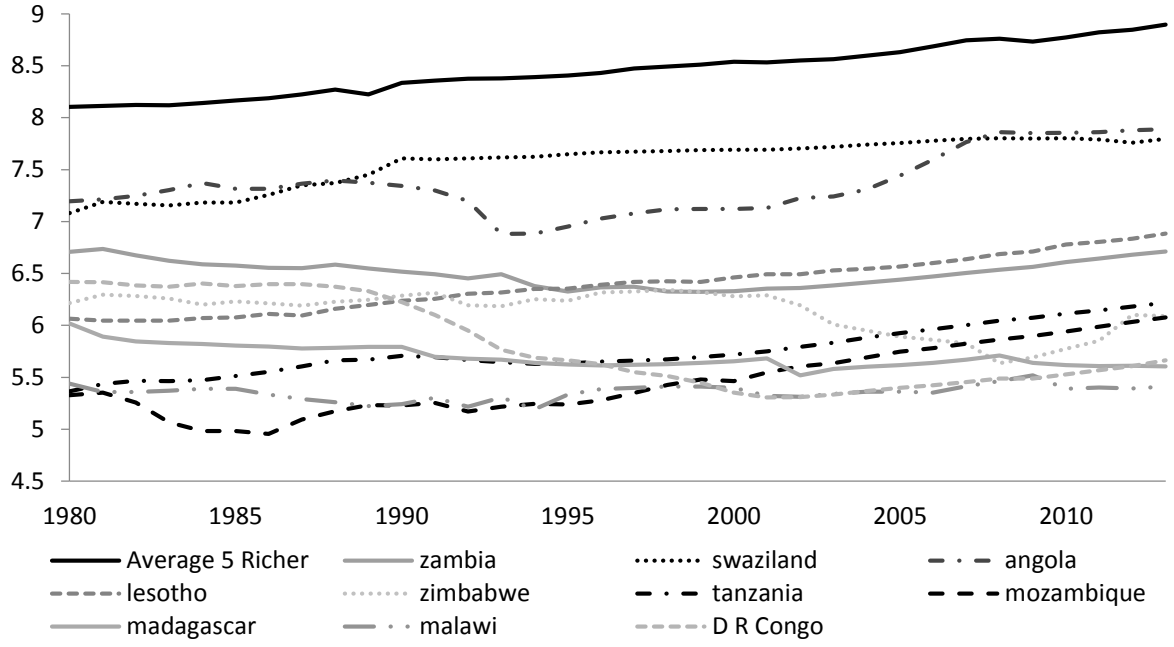

Table 1 Results of the five richer countries

1.1 Linear Model

Divergence vs Convergence	Absolute vs Conditional Convergence
0.0000	0.2000
Convergence	**Absolute**

1.2 TAR Model

Linearity Test		Transition Country	d	λ	% Observation in Regime I
Unrestricted	Restricted				
0.0070	0.0040	Botswana	1	5.47	83.87

Convergence Tests

Divergence vs Convergence			Absolute vs Conditional Convergence		
Regime I	Regime II	Both	Regime I	Regime II	Both
0.0010	0.0160	0.0000	0.2230	0.0330	0.0360
Full Convergence			Absolute under regime I and Conditional under regime II		

Note: Entries refer to bootstrap p-values computed as described in the paper. The selected lag length is 1 has chosen by the Ljung-Box statistic.

Table 2 Results of the average of five richer and the middle countries

2.1 Linear Model

Divergence vs Convergence	Absolute vs Conditional Convergence
0.0430	0.3510
Convergence	Absolute

2.2 TAR Model

Linearity Test		Transition Country	d	λ	% Observation in Regime I
Unrestricted	Restricted				
0.2370	0.2220	-	-	-	-

Convergence Tests

Divergence vs Convergence			Absolute vs Conditional Convergence		
Regime I	Regime II	Both	Regime I	Regime II	Both
-	-	-	-	-	-

Note: Entries refer to bootstrap p-values computed as described in the paper. 1 lag length is used.

Table 3 Results of the five richer and other SADC countries

3.1 Linear Model

Divergence vs Convergence	Absolute vs Conditional Convergence
0.2890	-
Divergence	-

3.2 TAR Model

Linearity Test		Transition Country	d	λ	% Observation in Regime I
Unrestricted	Restricted				
0.0050	0.0420	Angola	1	5.14	74.19

Convergence Tests

Divergence vs Convergence			Absolute vs Conditional Convergence		
Regime I	Regime II	Both	Regime I	Regime II	Both
0.5730	0.0060	0.0500	-	0.3590	-
Partial Convergence Regime II					

Note: Entries refer to bootstrap p-values computed as described in the paper. 1 lag length is used.

Table 4 Results CMA countries

4.1 Linear Model

Divergence vs Convergence	Absolute vs Conditional Convergence
0.0890	0.6350

4.2 TAR Model

Linearity Test		Transition Country	d	λ	% Observation in Regime I
Unrestricted	Restricted				
0.1540	0.1580	-	-	-	-

Convergence Tests

Divergence vs Convergence			Absolute vs Conditional Convergence		
Regime I	Regime II	Both	Regime I	Regime II	Both
-	-	-	-	-	-

Note: Entries refer to bootstrap p-values computed as described in the paper. 1 lag length is used.

Table 5 Results SACU countries

5.1 Linear Model

Divergence vs Convergence	Absolute vs Conditional Convergence
0.0000	0.0250

5.2 TAR Model

Linearity Test		Transition Country	d	λ	% Observation in Regime I
Unrestricted	Restricted				
0.0550	0.0710	-	-	-	-

Convergence Tests

Divergence vs Convergence			Absolute vs Conditional Convergence		
Regime I	Regime II	Both	Regime I	Regime II	Both
-	-	-	-	-	-

Note: Entries refer to bootstrap p-values computed as described in the paper. 1 lag used.