# Does Africa grow slower than Asia and Latin America?

Richard Paap[*]
*Econometric Institute*
*Erasmus University Rotterdam*

Philip Hans Franses[†]
*Econometric Institute*
*Erasmus University Rotterdam*

Dick van Dijk[‡]
*Econometric Institute*
*Erasmus University Rotterdam*

Econometric Institute Report EI 2003-07

February 2003

**Abstract**

In this paper we address the question whether countries on the African continent have lower average growth rates in real GDP per capita than countries in Asia and Latin America. In contrast to previous studies, we do not aggregate the data, nor do we *a priori* assign countries to clusters. Instead, we put forward a so-called latent class panel time series model, which allows a data-based classification of countries to clusters with growth levels that differ across the clusters. Our empirical results suggest that twenty-six African countries can be assigned to the low growth cluster, but that eleven African countries show growth levels which are comparable with many countries in Asia and Latin America. We also present results for sub-periods, which demonstrate that the relative performance of African countries has improved considerably over time.

**Key words:** Economic growth; panel time series; latent class models
**JEL Classification Code:** C32 C33 O4 O57

[*]Econometric Institute, Erasmus University Rotterdam, P.O. Box 1738, NL-3000 DR Rotterdam, The Netherlands, email: paap@few.eur.nl

[†]Econometric Institute, Erasmus University Rotterdam, P.O. Box 1738, NL-3000 DR Rotterdam, The Netherlands, email: franses@few.eur.nl (corresponding author)

[‡]Econometric Institute, Erasmus University Rotterdam, P.O. Box 1738, NL-3000 DR Rotterdam, The Netherlands, email: djvandijk@few.eur.nl

# 1 Introduction

This paper aims to answer the question whether countries on the African continent grow slower, in terms of real GDP per capita, than countries in Asia and Latin America. It is an often-heard statement that Africa is the "lost continent". However, it is unclear whether this statement applies to all African countries or to just a specific group of countries. When we consider the literatures on poverty, on growth, and on convergence, we observe that in almost all studies one includes a 0-1 dummy variable for Africa in a specific regression model, essentially implying that *all* countries on this continent have a similar economic performance. Exceptions are for example Quah (1997) and Paap and van Dijk (1998), which allow for endogenous clustering of countries, based on some measure of economic performance. These studies however do not aim to answer the question in the title. Hence, in this paper we focus on the question whether Africa grows slower than Asia and South America while allowing for endogenous group formation.

It is important to understand the differences in growth rates across countries, as economic growth is of tantamount importance for poverty reduction, see for example Dollar and Kraay (2002). Also, it is important to examine if poverty is increasing or not, see for example, Chen, Datt and Ravallion (1994). Knowing which countries get poorer, relative to other countries, also allows one to study the origins of these negative developments. Possible reasons for (increasing) poverty are political instability, geographic location, lack of free trade, dictatorship and social conflicts, see Easterly and Levine (1997), for example.

Even though on average African countries may be have been showing worse economic performance than, say, Asian and Latin American countries, it is not clear *a priori* whether this holds for *all* countries on the continent. It may well be that certain African countries in some sense look more like Asian or Latin American countries in terms of economic development, and bear little similarities with neighboring countries on the same continent. Comparing growth performance of individual countries across continents makes it possible to examine this possibility.

An important strand of the literature on (relative) economic growth concerns an investigation of the so-called convergence hypothesis. Convergence would imply that the poor catch up with the rich, and hence in the long run one might hope to have no poor countries anymore. The convergence literature describes a wide range of techniques to examine this hypothesis for various types of data. There are regression-based methods and distribution-based methods, see for example Barro and Sala-i-Martin (1992), Quah (1996, 1997), Paap and van Dijk (1998), and the excellent survey in Durlauf and Quah (1999).

It seems that the general conclusion from all these studies is that there is no worldwide convergence, and that there are even indications for divergence. If there is any evidence of convergence, then it is typically found that there are so-called “convergence clubs”. It is important to remark here that the model we propose below, to investigate whether Africa is growing slower than for example Asia, can be applied in case of convergence, in case of divergence and in case of convergence clubs. In that sense, our methodology is rather robust to the type and degree of convergence, if there is any. Indeed, we will examine if there are clusters of countries with similar growth rates. Whether there is convergence or not depends on the starting levels of the country-specific real GDP per capita. Our results are indifferent to these initial levels.

As many other studies, the data set we use to examine common properties across growth rates is the Penn World Tables (version 6.1). These tables cover annual data on a range of economic variables, and we focus on annual growth rates of real GDP per capita over the period from 1960 to 2000. The selected sample period implies that we cannot use all countries in Africa, Asia and Latin America, but just a total of 69 of these. Our data set thus amounts to a panel of time series, where both the time series $T$ and the cross-section dimension $N$ are fairly large. Our model tries to summarize these data in a concise manner, such that we can answer the question in the title.

Unrestricted analysis of 69 models for the country-specific growth rates might not be very informative. First of all, one might expect that the error variables in these models have non-zero covariance. However, applying seemingly unrelated regression techniques is not possible, as we cannot estimate an unrestricted full rank 69 by 69 dimensional covariance matrix given that we only have 41 observations per country. One way out of this dilemma is to simply assume that the errors are uncorrelated, although this would be quite unrealistic. An alternative approach is to assume that the errors, say, $u_{i,t}$ for country $i$ at time $t$, can be related to a set of common determinants as $u_{i,t} = z_t'\alpha_i + \varepsilon_{i,t}$, where the $\varepsilon_{i,t}$ have a diagonal covariance matrix. The linear combination $z_t'\alpha_i$ then transfers the contemporaneous correlation from the errors to the conditional expectation part of the model. In our empirical analysis we take as $z_t$ the demeaned growth rate in US per capita real GDP, which might measure something like a “world business cycle”.

Turning back to the conditional expectations, unrestricted estimation of 69 equations would deliver 69 growth rates, and to group these into, say, large and small values, while accounting for their standard errors, is not trivial. One way to handle this problem is to pool the parameters over all models or over pre-assigned subsets of these equations. Indeed, given the question in the title, one would be tempted to form three clusters according to the different continents involved in the analysis. This however would be more or less equivalent to including dummies for the different continents in a pooled regression, as discussed above, and is subject to our own criticism of such methods. Hence, we prefer to let the data decide if any clusters exist, and what the key properties of these clusters are. Hobijn and Franses (2000) propose a clustering method, but it is found that this method leads to (too) many clusters. This might be due to the fact that their method involves many statistical tests, and it is therefore not easy to control the overall size.

In this paper we propose a new methodology. Our approach aims to summarize the information in the panel of time series in a concise manner, while allowing for the possibility that countries show similar behavior. We assume that each country has some probability of getting assigned to a latent class, within which the countries have the same economic growth, while growth rates are different across clusters. The data should tell us which countries belong to which class, and also how many classes there are. We call our model a latent class panel time series model.

The outline of our paper is as follows. In Section 2, we introduce the model we use in our empirical work. For future purposes, we describe estimation and inference for a slightly more general version of it. In Section 3, we discuss the data we use for our empirical analysis and present the estimation results. One of our key findings, which is partly in contrast to what one might have expected, is that twenty-six African countries can be assigned to the low growth clusters, but that eleven African countries show growth levels which are comparable with various countries in Asia and Latin America. In Section 4, we conclude with some remarks.

# 2 Methodology

This section contains a discussion of the representation of the latent class panel time series model. Next, it presents a method to estimate the model parameters. Finally, we discuss the interpretation of the model and its parameters. Throughout, we focus on the practical application of the model in this paper. However, we discuss the estimation method for a more general model, for future purposes.

## 2.1 The model

Before we present and analyze a general representation of the model, we first give the model as we will use it in the empirical section below to provide relevant insights. Consider the growth rate of real GDP per capita, as measured by the first differences of the natural logarithms of the level series, for country $i$ in year $t$, to be denoted as $y_{i,t}$. We will deal with $N = 69$ countries from Africa, Asia and Latin America. To capture the contemporaneous correlation among growth rates in different countries, we choose to include in each of the 69 equations the growth rate in US GDP per capita, to be denoted as $z_t$. This variable is demeaned prior to the analysis, so that it does not interact with the country-specific mean growth rates. Next, we assume that each country-specific average growth rate, after correction for the growth rate in the US, is equal to $\mu_j$, where this mean can take $J$ different values with probability $p_j$, $j = 1, 2, \ldots, J$. That is, we assume that the country-specific growth rates (after correction for US growth) can be classified into $J$ clusters. Finally, the demeaned growth rate for each individual country is assumed to obey an autoregression of order $K$.

In sum, our model to be analyzed for the annual GDP growth rates in the next section is

$$y_{i,t} - \mu_{s_i} - \alpha_i z_t = \sum_{k=1}^{K} \rho_{ik}(y_{i,t-k} - \mu_{s_i} - \alpha_i z_{t-k}) + \varepsilon_{i,t} \tag{1}$$

with $\varepsilon_{i,t} \sim \mathrm{N}(0, \sigma_i^2)$ for $i = 1, \ldots, N$ and $t = 1, \ldots, T$. In our case, $N = 69$ and $T = 40$. The $s_i \in \{1, \ldots, J\}$ with

$$\Pr[s_i = j] = p_j \qquad \text{with} \sum_{j=1}^{J} p_j = 1. \tag{2}$$

In the end, the main interest lies in the number of clusters $J$ and in the average growth rates $\mu_1, ..., \mu_J$ in each of the $J$ clusters. Note that the values of $\mu_1, ..., \mu_J$, as well as the cluster probabilities $p_1, \ldots, p_J$, are parameters to be estimated, along with $\alpha_i$, $\sigma_i^2$ for $i = 1, \ldots, N$, and $\rho_{ik}$ for $i = 1, \ldots, N$, $k = 1, \ldots, K$.

The above model is a specific version of the more general latent class panel time series model given by

$$y_{i,t} - x'_{i,t}\beta_{s_i} - z'_{i,t}\alpha_i = \sum_{k=1}^{K} \rho_{ik}(y_{i,t-k} - x'_{i,t-k}\beta_{s_i} - z'_{i,t-k}\alpha_i) + \varepsilon_{i,t} \tag{3}$$

with $x_{i,t}$ a $(m \times 1)$ vector of exogenous variables, $\varepsilon_{i,t} \sim \mathrm{N}(0, \sigma_i^2)$ for $i = 1, \ldots, N$ and $t = 1, \ldots, T$, and $s_i \in \{1, \ldots, J\}$ with cluster probabilities given in (2). The generality of this representation follows from the fact that it allows for multiple determinants of growth to be included through the term $x'_{i,t}\beta_{s_i}$ instead of just $\mu_{s_i}$, see Barro (1991), Levine and Renelt (1992), Sala-i-Martin (1997), and Temple (1999), among many others, for possible choices of such variables. Furthermore, $z_{i,t}$ could also include country-specific variables. In words, the $N$ countries can be clustered according to the effects of $x_{i,t}$ on $y_{i,t}$.

One can use the Schwarz/Bayesian Information Criterion (BIC) to make a choice concerning the appropriate value of $J$. The same information criterion can be used to decide upon the value of the lag order $K$.

## 2.2 Parameter estimation

To estimate the parameters of the general latent class panel time series model we use the EM algorithm of Dempster, Laird and Rubin (1977), see also McLachlan and Krishnan (1997). This estimation method is an iterative algorithm which provides a maximum of the log-likelihood function. In the first step (E-step) one takes the conditional expectation of the log of the complete data likelihood function with respect to the latent variables. In the second step (M-step) one maximizes this expected log-likelihood function over the model parameters. One repeats these two steps until convergence occurs. The resulting estimate is equal to the Maximum Likelihood [ML] estimate.

The likelihood function of the mixture panel model (3) is given by

$$l(y;\theta) = \prod_{i=1}^{N}\left(\sum_{j=1}^{J} p_j \left(\prod_{t=1}^{T} \frac{1}{\sigma_i}\phi(\varepsilon_{i,t}/\sigma_i)\right)\right), \tag{4}$$

where $\theta$ summarizes the model parameters, where $y = \{\{y_{i,t}\}_{t=1}^{T}\}_{i=1}^{N}$, and where $\phi(\cdot)$ denotes the probability density function of a standard normal variable. The complete data likelihood function is given by

$$l(y,s;\theta) = \prod_{i=1}^{N}\left(\prod_{j=1}^{J}\left(p_j \prod_{t=1}^{T} \frac{1}{\sigma_i}\phi(\varepsilon_{i,t}/\sigma_i)\right)^{I[s_i=j]}\right), \tag{5}$$

where it is assumed that the value of $s = (s_1, \ldots, s_N)$ is known. The expectation of the complete data log-likelihood function with respect to $s|y$ is given by

$$\mathcal{L}(y;\theta) = \sum_{i=1}^{N}\left(\sum_{j=1}^{J} p^*_{ij}\left(\sum_{t=1}^{T} -\frac{1}{2}\ln\sigma_i^2 - \frac{1}{2}\ln 2\pi - \frac{(\varepsilon^j_{i,t})^2}{2\sigma_i^2}\right)\right), \tag{6}$$

where $p^*_{ij}$ denotes the conditional probability that country $i$ belongs to cluster $j$, $\Pr[S_i = j|y_{i1}, \ldots, y_{i,T}; \theta]$, given by

$$p^*_{ij} = \frac{p_j \prod_{t=1}^{T} \frac{1}{\sigma_i}\phi(\varepsilon^j_{i,t}/\sigma_i)}{\sum_{l=1}^{J} p_j(\prod_{t=1}^{T} \frac{1}{\sigma_i}\phi(\varepsilon^l_{i,t}/\sigma_i))}, \tag{7}$$

where $\varepsilon^j_{i,t}$ denotes the residual of series $i$ at time $t$ in cluster $j$ and is defined as

$$\varepsilon^j_{i,t} = \tilde{y}_{i,t} - \tilde{x}'_{i,t}\beta_j - \tilde{z}'_{i,t}\alpha_i, \tag{8}$$

where we use

$$\begin{aligned} \tilde{y}_{i,t} &= y_{i,t} - \textstyle\sum_{k=1}^{K} \rho_{ik} y_{i,t-k} & \tilde{x}_{i,t} &= x_{i,t} - \textstyle\sum_{k=1}^{K} \rho_{ik} x_{i,t-k} \\ \tilde{z}_{i,t} &= z_{i,t} - \textstyle\sum_{k=1}^{K} \rho_{ik} z_{i,t-k} & \tilde{u}^j_{i,t} &= y_{i,t} - x'_{i,t}\beta_j - \alpha'_i z_{i,t} \end{aligned}$$

and $\bar{u}^j_{i,t} = (\tilde{u}^j_{i,t-1}, \ldots, \tilde{u}^j_{i,t-k})'$ to simplify the notation in the remainder of this section.

The first-order conditions for maximizing the expectation of the complete data log-likelihood function are given by

$$\frac{\partial \mathcal{L}(y;\theta)}{\partial \beta_j} = \sum_{i=1}^{N} \left( \frac{p^*_{ij}}{\sigma^2_i} \left( \sum_{t=1}^{T} \tilde{x}_{i,t}(\tilde{y}_{i,t} - \tilde{x}'_{i,t}\beta_j - \tilde{z}'_{i,t}\alpha_i) \right) \right) = 0 \quad \text{for } j = 1, \ldots, J, \tag{9}$$

and

$$\frac{\partial \mathcal{L}(y;\theta)}{\partial \alpha_i} = \sum_{j=1}^{J} \frac{p^*_{ij}}{\sigma^2_i} \left( \sum_{t=1}^{T} \tilde{z}_{i,t}(\tilde{y}_{i,t} - \tilde{x}'_{i,t}\beta_j - \tilde{z}'_{i,t}\alpha_i) \right) = 0 \qquad \text{for } i = 1, \ldots, N, \tag{10}$$

$$\frac{\partial \mathcal{L}(y;\theta)}{\partial \rho_i} = \sum_{j=1}^{J} \frac{p^*_{ij}}{\sigma^2_i} \left( \sum_{t=1}^{T} \bar{u}^j_{i,t}\varepsilon^j_{i,t} \right) = 0 \qquad \text{for } i = 1, \ldots, N, \tag{11}$$

$$\frac{\partial \mathcal{L}(y;\theta)}{\partial \sigma^2_i} = \sum_{j=1}^{J} p^*_{ij} \left( \sum_{t=1}^{T} -\frac{1}{2}\frac{1}{\sigma^2_i} + \frac{1}{2}\frac{(\varepsilon^j_{i,t})^2}{\sigma^4_i} \right) = 0 \qquad \text{for } i = 1, \ldots, N, \tag{12}$$

where $\rho_i = (\rho_{i1}, \ldots, \rho_{iK})'$. The solution to these first-order conditions are used in the Maximization step of the EM algorithm. Given the structure of the model it is convenient to use a Cochrane and Orcutt (1949) type of estimation method to maximize the expected log-likelihood function.

The resulting estimation algorithm can be summarized as follows:

1. Given the current estimates of the model parameters compute the posterior probabilities in (7).

2. Given the current estimates of $\beta_j$, update the estimates of $\alpha_i$, $\rho_i$ and $\sigma_i$ using the solutions to the first order conditions (10)-(12)

$$\alpha_i = \left(\sum_{t=1}^{T} \tilde{z}_{i,t}\tilde{z}'_{i,t}\right)^{-1} \left(\sum_{j=1}^{J} p^*_{ij} \sum_{t=1}^{T} \left((\tilde{y}_{i,t} - \tilde{x}'_{i,t}\beta_j)\tilde{z}'_{i,t}\right)\right) \quad \text{for } i = 1, \ldots, N, \tag{13}$$

$$\rho_i = \left(\sum_{j=1}^{J} p^*_{ij} \sum_{t=1}^{T} \left(\bar{u}^j_{i,t}(\bar{u}^j_{i,t})'\right)\right)^{-1} \left(\sum_{j=1}^{J} p^*_{ij} \sum_{t=1}^{T} \left(\tilde{u}^j_{i,t}(\bar{u}^j_{i,t})'\right)\right) \text{ for } i = 1, \ldots, N, \tag{14}$$

$$\sigma_i^2 = \frac{\sum_{t=1}^{T}\sum_{j=1}^{J} p^*_{ij}(\varepsilon^j_{i,t})^2}{T} \quad \text{for } i = 1, \ldots, N. \tag{15}$$

3. Given the new estimates of $\alpha_i$, $\sigma_i^2$ and $\rho_i$, update the estimates of $\beta_j$ using the solutions to the first order conditions (9) as

$$\beta_j = \left(\sum_{i=1}^{N}\sum_{t=1}^{T} \left(\frac{p^*_{ij}}{\sigma_i^2}\tilde{x}_{i,t}\tilde{x}'_{i,t}\right)\right)^{-1} \left(\sum_{i=1}^{N}\sum_{t=1}^{T} \left(\frac{p^*_{ij}}{\sigma_i^2}(\tilde{y}_{i,t} - \tilde{z}'_{i,t}\alpha_i)\tilde{x}'_{i,t}\right)\right) \text{ for } j = 1, \ldots, J. \tag{16}$$

4. Finally, update the $p_j$ parameters using

$$p_j = \frac{\sum_{i=1}^{N} p^*_{ij}}{N} \quad \text{for } j = 1, \ldots, J. \tag{17}$$

5. If no convergence goto step 1.

As convergence criterion, one may use the change in the log-likelihood value or the (relative) change in the parameter values. Note that we do not perform a full maximization in steps 2-4. One may of course repeat steps 2-4 several times until one obtains convergence, but it turns out that this is not necessary for the algorithm to work. A convenient way to start up this algorithm is to use random numbers on the $[0, 1]$ interval as starting values for the probabilities $p^*_{ij}$. Finally, the ML estimator (obtained using the EM algorithm) is asymptotically normal distributed with as mean the true value of $\theta$ and the covariance equal to the inverse of the information matrix of the likelihood function (5). To compute standard errors for the mean values in cluster $J$, the information matrix is estimated by evaluating the Hessian in the ML parameter estimate.

## 2.3 Interpretation

We now say a few words about how one interprets the model and its parameters, where the focal interest is in the values of $J$ and $p^*_{ij}$.

When $J = 1$, there is only one cluster and the model implies that all countries have the same average growth rate, at least after correction for country-specific correlation with the US economy. Note that this does not imply convergence or divergence, as this would depend on the starting levels of the real GDP per capita series.

When $J = N = 69$, the number of clusters equals the number of countries, and the resultant model is the well-known fixed-effects panel model. In this case it is not possible to form clusters of countries with statistically similar growth rates.

Finally, when $J$ takes a value in between 1 and $N$=69, clusters of countries with similar growth rates are identified. The probabilities $p_{ij}^*$ in (7) evaluated at the ML parameter estimates provide direct information on the cluster membership of the individual countries, as they merely are estimates of the probability that country $i$ belongs to cluster $j$. Hence, based on these probabilities one can assign each country to a particular cluster, for example.

# 3 Application

In this section, we apply the specific version of the model, that is (1) with (2) to our data set consisting of annual growth rates in real GDP per capita. Our choice for this simpler model is guided by data limitations, but of course, more general versions can be entertained. We first discuss the data, and next we give detailed empirical results, for the full sample period as well as for sub-periods.

We obtained real GDP per capita from the Penn World Tables, version 6.1. for the 69 countries presented in Table 1. These are 37 countries in Africa, 18 in Asia and 14 in Latin America. The choice for these particular countries was guided by data availability, where the main restriction was the access to four decades of observations, starting in 1960 and ending in 2000. We constructed the country-specific growth rates by taking first differences of the log levels. As the observation for 1960 is lost due to the construction of growth rates, each time series consists of $T = 40$ observations.

In order to use the model in (1), we need to decide upon the number of clusters $J$ and the order of the autoregression $K$. We estimate models where $J$ can take the values 1, 2, 3, 4, and 69, and where $K$ can be 0 or 1. We report the values of the BIC for each of those models in Table 2, where the variation is due to the way we count the number of observations in the model selection criteria, either as $NT$ or as $N$, respectively. We observe that in both cases the minimum BIC values are obtained for $J = 3$, and that there are not many differences across the static ($K = 0$) and dynamic ($K = 1$) case. In our further analysis, we therefore focus on the $K = 0$ case as this also allows for more degrees of freedom, and hence more statistical precision.

Table 3, which concerns the full sample estimates, shows that 7 of the 69 countries have the highest probability of getting assigned to the cluster with the highest average growth rate, which equals 4.3 percent per annum. Six of these 7 countries are Asian. There are twenty-six African countries in the low growth cluster, where average growth is equal to less than 0.5 percent per year (but still significantly positive). Notice also that 7 of the 14 Latin American countries are assigned to this low growth class. Interestingly, there are 11 African countries which can be assigned to the middle growth class, which has an average annual growth of 2.22 percent. Hence, one-in-three African countries seems to have been doing reasonably well.

To see if these full sample results continue to hold in sub-periods, we repeat the analysis for four of these, each spanning 10 years. The results of this analysis are given in Table 4. We observe that from 1981 onwards there are many countries which suffer from negative growth. Whereas the estimate of mean growth rate in the low growth cluster is significantly positive for the 1960s and 1970s, it becomes significantly negative for the 1980s and 1990s, and the number of countries assigned to these clusters equals 39 and 21, respectively. On the other hand, over time, more and more African countries can be assigned to the middle and high growth clusters. The number of African countries in the high growth cluster shows a remarkable increase from 2 to 7 during the second part of the sample, while the number of African countries in the middle class jumps to 13 in the 1990s from 4-5 in earlier decades. Obviously, the classifications “high growth”, “middle growth” and “low growth” are relative measures, as the absolute growth rates have decreased over the years for all three classes. Indeed, the average growth rates in both the high and middle classes have decreased substantially in the last two decades. The (relative) performance of both Asian and Latin American countries also has been improving over time. For example, while Asian countries are spread over the three classes more or less equally for the first two decades, they are increasingly assigned to the high and middle growth clusters during the last two decades. For the Latin American countries a similar trend is visible.

The results in Table 4 can also be summarized along other lines. Using the transitions of countries to different clusters from one decade to another, one can compute the long-run equilibrium distribution of countries over the three clusters. The outcome of this exercise appears in Table 5. The stable solutions clearly show improvement over time. Based on the transitions between the 1960s and the 1970s, we find an equilibrium which implies that more than 60% of the countries would eventually end up in the low growth cluster. The equilibrium solution associated with the transitions between the 1970s and 1980s, shows a sharp distinction between two groups of countries of about equal size in the high and low clusters, with less than 10% of the countries in the middle class. The final stable solution perhaps is more realistic as it implies that, approximately, one out of four countries shows low (or negative) growth, one out of four countries has middle growth, while two out of four countries shows high growth.

# 4 Conclusion

In this paper we have proposed to analyze the relative performance, in terms of growth rates in real GDP per capita, of a large number of countries in Africa, Asia and Latin America. One of the main assumptions underlying our analysis is the possibility that there would be clusters of countries with similar economic performance. However, we did not want to decide *a priori* on the number and size of these clusters, let alone assign individual countries to particular countries exogenously. For this reason we put forward a latent class panel time series model, which allows for endogenous clustering of countries. To enable alternative uses of this model, we described an estimation routine for a more general version of the model than the one used in our empirical analysis.

An important conclusion from our empirical analysis is that, relatively speaking, not all included African countries are performing poorly. Indeed, one out of three African countries has growth rates which match those of many Asian and Latin American countries. The sub-sample analysis shows that the performance of quite a few African countries has improved over time. Hence, our model demonstrates its usefulness by indicating that there are no continent-specific clusters.

In our future research, we plan to rely on a similar model to analyze indicators of performance, other than purely economic ones. It may be that alternative measures of living standards can shed new light on development issues.

Table 1: Countries involved in the empirical analysis

| Africa | Asia | Latin America |
|---|---|---|
| Algeria | Bangladesh | Argentina |
| Burundi | China | Barbados |
| Benin | Hong Kong | Bolivia |
| Burkina Faso | Indonesia | Brazil |
| Cape Verde | India | Chili |
| Congo | Iran | Colombia |
| Cote D'Ivoire | Israel | Dominican Republic |
| Cameroon | Japan | Ecuador |
| Comoros | Jordan | Jamaica |
| Egypt | Korea | Paraguay |
| Ethiopia | Malaysia | Peru |
| Gabon | Nepal | Trinidad and Tobago |
| Ghana | Pakistan | Uruguay |
| Guinea | Philippines | Venezuela |
| Gambia | Sri Lanka | |
| Guinea-Bissau | Syria | |
| Equatorial Guinee | Thailand | |
| Kenia | Turkey | |
| Lesotho | | |
| Madagascar | | |
| Malawi | | |
| Mali | | |
| Mauritius | | |
| Morocco | | |
| Mozambique | | |
| Niger | | |
| Nigeria | | |
| Rwanda | | |
| Senegal | | |
| Seychelles | | |
| Chad | | |
| Togo | | |
| Tanzania | | |
| Uganda | | |
| South Africa | | |
| Zambia | | |
| Zimbabwe | | |

Table 2: Selecting the number of latent classes $J$ using BIC[1].

| Model | $J = 1$ | $J = 2$ | $J = 3$ | $J = 4$ | $J = 69$ |
|---|---|---|---|---|---|
| | *BIC based on total number of observations* $NT = 69 \times 40$ | | | | |
| Static | $-2.525$ | $-2.555$ | $-2.559$ | $-2.556$ | $-2.435$ |
| Dynamic | $-2.438$ | $-2.440$ | $-2.436$ | $-2.432$ | $-2.302$ |
| | *BIC based on number of series* $N = 69$ | | | | |
| Static | $-108.431$ | $-109.732$ | $-110.012$ | $-109.974$ | $-108.469$ |
| Dynamic | $-106.111$ | $-106.321$ | $-106.242$ | $-106.211$ | $-104.425$ |

[1] The model with minimum value of the criterion is to be preferred.

Table 3: Classification results, based on full-sample estimates of a static model with three latent classes, with numbers of countries per continent assigned to clusters with specific annual percentage growth rates. The estimated standard error of the cluster-specific mean growth rates appear in parentheses

| Cluster | $\widehat{\mu}_j$ (s.e.) | Africa | Asia | Latin America |
|---|---|---|---|---|
| High growth | 4.344 (0.270) | 0 | 6[1] | 1[2] |
| Middle growth | 2.221 (0.189) | 11[3] | 9[4] | 6[5] |
| Low growth | 0.446 (0.200) | 26[6] | 3[7] | 7[8] |

[1] China, Hong Kong, Japan, Korea, Malaysia, and Thailand.
[2] Barbados.
[3] Algeria, Congo, Cape Verde, Egypt, Gabon, Lesotho, Morocco, Mauritius, Malawi, Seychelles, and Zimbabwe.
[4] Indonesia, India, Iran, Israel, Sri Lanka, Nepal, Pakistan, Syria, and Turkey.
[5] Brazil, Chili, Colombia, Dominican Republic, Paraguay, and Trinidad and Tobago.
[6] Burundi, Benin, Burkina Faso, Cote D'Ivoire, Cameroon, Comoros, Ethiopia, Ghana, Guinea, Gambia, Guinea-Bissau, Equatorial Guinee, Kenia, Madagascar, Mali, Mozambique, Niger, Nigeria, Rwanda, Senegal, Chad, Togo, Tanzania, Uganda, South Africa, and Zambia.
[7] Bangladesh, Jordan, and Philippines.
[8] Argentina, Bolivia, Ecuador, Jamaica, Peru, Uruguay, and Venezuela.

Table 4: Classification results based on a static model with three latent classes for different sub-periods, with number of countries per continent assigned to clusters with specific annual percentage growth rates

| Cluster | $\widehat{\mu}_j$ (s.e.) | Africa | Asia | Latin America |
|---|---|---|---|---|
| 1961-1970 | | | | |
| High growth | 5.721 (0.844) | 1 | 5 | 0 |
| Middle growth | 3.265 (0.202) | 4 | 4 | 6 |
| Low growth | 1.406 (0.160) | 32 | 9 | 8 |
| 1971-1980 | | | | |
| High growth | 5.462 (0.342) | 2 | 4 | 3 |
| Middle growth | 3.101 (0.209) | 5 | 6 | 5 |
| Low growth | 0.831 (0.250) | 30 | 8 | 6 |
| 1981-1990 | | | | |
| High growth | 3.711 (0.201) | 7 | 12 | 1 |
| Middle growth | 1.191 (0.444) | 4 | 1 | 5 |
| Low growth | -0.753 (0.329) | 26 | 5 | 8 |
| 1991-2000 | | | | |
| High growth | 3.001 (0.196) | 7 | 13 | 6 |
| Middle growth | 1.259 (0.170) | 13 | 5 | 4 |
| Low growth | -0.765 (0.198) | 17 | 0 | 4 |

Table 5: Stable solutions for cluster probabilities associated with transition matrices for different sub-periods[1]

| Cluster | 61-70 to 71-80 | 71-80 to 81-90 | 81-90 to 91-00 |
|---|---|---|---|
| High growth | 0.151 | 0.408 | 0.473 |
| Middle growth | 0.239 | 0.075 | 0.290 |
| Low growth | 0.611 | 0.516 | 0.237 |

[1] The numbers in this table are based on the following computations. We count the number of countries in the three clusters in period $T-1$ and in period $T$. These numbers are collected in a $3 \times 3$ matrix, say, $P$. All numbers are divided by 69 to obtain "transition probabilities" of going from cluster $i$ to cluster $j$. Next, we compute the long-run cluster probabilities in the $3 \times 1$ vector $\pi$ by solving $P\pi = \pi$.

# References


Barro, R.J. (1991), Economic Growth in a Cross Section of Countries, *Quarterly Journal of Economics* **56**, 407–443.

Barro, R.J. and X. Sala-i-Martin (1992), Convergence, *Journal of Political Economy* **100**, 223–251.

Brock, W.A. and S.N. Durlauf (2001), Growth Empirics and Reality, *The World Bank Economic Review* **15**, 229–272.

Chen, S.H., G. Datt and M. Ravallion (1994), Is Poverty Increasing in the Developing World?, *Review of Income and Wealth* **4**, 359–376.

Cochrane, D. and Orcutt, G. H. (1949), Application of Least Squares Regressions to Relationships Containing Autocorrelated Error Terms, *Journal of the American Statistical Association* **44**, 32–61.

Dempster, A.P., N.M. Laird and R.B. Rubin (1977), ML Estimation from Incomplete Data via the EM algorithm (with discussion), *Journal of the Royal Statistical Society* **B 39**, 1–38.

Dollar, D. and A. Kraay (2002), Growth is Good for the Poor, *Journal of Economic Growth* **7**, 195–225.

Durlauf, S.N. and P. Johnson (1995), Multiple Regimes and Cross-Country Growth Behavior, *Journal of Applied Econometrics* **10**, 365–384.

Durlauf, S.N. and D.T. Quah (1999), The New Empirics of Economic Growth, in J.B. Taylor and M. Woodford (eds.), *Handbook of Macroeconomics Vol. 1A*, Amsterdam: North-Holland, pp. 231–304.

Easterly, W. and R. Levine (1997), Africa's Growth Tragedy: Policies and Ethnic Divisions, *Quarterly Journal of Economics* **58**, 1203–1250.

Hobijn B, and P.H. Franses (2000), Asymptotically Perfect and Relative Convergence of Productivity, *Journal of Applied Econometrics* **15**, 59–81.

Levine, R. and D. Renelt (1992), A Sensitivity Analysis of Cross-Country Growth Regressions, *American Economic Review* **75**, 308–313.

McLachlan, G.J. and T. Krishnan (1997), *The EM Algorithm and Extensions*, New York: John Wiley & Sons.

Paap, R. and H.K. van Dijk (1998), Distribution and Mobility of Wealth of Nations, *European Economic Review* **42**, 1269–1293.

Pesaran, M.H, Y.C. Shin and R.P. Smith (1999), Pooled Mean Group Estimation of Dynamic Heterogeneous Panels, *Journal of American Statistical Association* **94**, 621–634.

Quah, D.T. (1996), Empirics for Economic Growth and Convergence, *European Economic Review* **40**, 1353–1375.

Quah, D.T. (1997), Empirics for Growth and Distribution: Stratification, Polarization and Convergence Clubs, *Journal of Economic Growth* **2**, 27–59.

Sala-i-Martin, X. (1997), I Just Ran 2 Million Regressions, *American Economic Review* **80**, 178–183.

Temple, J. (1999), The New Growth Evidence, *Journal of Economic Literature* **37**, 112–156.