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Structural Differences in Economic Growth: An Endogenous Clustering Approach*

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Abstract

This paper addresses heterogeneity in determinants of economic growth in a data-driven way. Instead of defining groups of countries with different growth characteristics a priori, based on, for example, geographical location, we use a finite mixture panel model and endogenous clustering to examine cross-country differences and similarities in the effects of growth determinants.

Applying this approach to an annual unbalanced panel of 59 countries in Asia, Latin and Middle America and Africa for the period 1971-2000, we can identify two groups of countries in terms of distinct growth structures. The structural differences between the country groups mainly stem from different effects of investment, openness measures and government share in the economy. Furthermore, the detected segmentation of countries does not match with conventional classifications in the literature.

Keywords: *Economic growth, parameter heterogeneities, latent class models, panel time series.*
JEL Classification: *C-32, C-33, O-4, O-57.*

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1 Introduction

The empirical literature on the analysis of growth determinants has provided substantial evidence for the existence of variations in growth patterns across countries. Despite this common finding, there is no agreed way of incorporating these variations in econometric models. There are several possibilities to allow for cross-country heterogeneity in the effects of growth determinants, and existing growth theories do not pinpoint a preferred method. It is common to capture heterogeneity by defining groups of countries with (presumably) different growth characteristics a priori, for example, based on geographical location. Using this approach, a number of empirical studies have examined whether growth patterns are different for countries in sub-Saharan Africa and East Asia (e.g. Barro, 1991; Easterly and Levine, 1997; Collier and Gunning, 1999), for landlocked countries (Sachs and Warner, 1997; Bloom *et al.*, 2003), or for former colonies (Barro, 1999).

Durlauf (2000) suggests that modeling cross-country heterogeneity is one of the main challenges in the current empirical growth literature, and points out two problems arising from the failure to control for heterogeneity in the right way. First, ad-hoc country groupings may simply be incorrect, in the sense that they may differ substantially from the true grouping. Second, most studies only allow variation in the intercept (which corresponds with the mean growth rate conditional on the included regressors), while restricting the effects of variables such as inflation and investment to be the same across (groups of) countries. Obviously, this assumption is quite restrictive. In fact, one of the most interesting questions is whether and how the effects of such growth determinants are country specific. Hence, it is emphasized that empirical research should focus on analyzing and documenting the heterogeneities in the countries' growth processes, see also Durlauf (2007).

In line with Durlauf's arguments, several recent empirical studies refrain from grouping countries beforehand, and mainly let the data classify the countries into clusters with distinct growth patterns. Two main approaches can be distinguished within these data-based clustering methods.

In the first approach, countries are grouped according to the values of one or more selected covariates. In the simplest possible case with two groups and a single covariate, the countries are assigned to one of the two groups depending on whether the value of the so-called splitting variable is below or above a certain threshold (see e.g. Durlauf and Johnson, 1995; Kalaitzidakis *et al.*, 2001; Hansen, 2000; Cuaresma and Doppelhofer, 2007). A possible drawback of this approach is that the splitting variable(s) still has (have) to be determined a priori. This is avoided in the second approach, called endogenous clustering (see e.g. Hobijn and Franses, 2000; Paap, Franses, and van Dijk, 2005). In this approach the clustering essentially is assumed to be a latent endogenous process and hence it is completely data-driven. The only prior assumption that needs to be made is that each country has some probability of getting assigned to a cluster. Within such a cluster countries have the same economic growth pattern, while this is different across the clusters. The data is allowed to determine which countries belong to which cluster and also how many clusters there are. Therefore the existence and the identification of heterogeneity of growth determinants is done without any prior specifications: We note that, consequently, any classification using regional dummies or other splitting variables are special cases of possible models compared in endogenous clustering.

Using the endogenous clustering approach, this paper aims to examine whether there are structural differences across countries in Asia, Latin and Middle America, and Africa in terms of their growth determinants, and if so, to identify the sources of these differences. We extend the clustering approach that is typically used in the convergence literature and in previous analysis of growth rate differences. Specifically, the countries are clustered not only according to their average growth rates but also according to the effects of growth determinants. Our method provides a systematic analysis of heterogeneity in growth patterns by allowing all regressors to have different marginal effects across clusters.

A few other recent studies apply alternative clustering methods in order to identify heterogeneities in growth determinants across countries. However, most of these studies, such as Durlauf and Johnson (1995) and Ardic (2006), use a two-step approach. In these methods, the country groups are determined before estimating the rest of the parameters, and marginal effects of growth determinants are then estimated within each group. Our analysis in this paper is more general as we determine the country groupings and parameter heterogeneities simultaneously, rather than identifying the country groups beforehand.

We apply our clustering approach to an unbalanced panel of annual growth rates for 59 countries from Asia, Africa, and Latin and Middle America for the period 1971 to 2000. We find 2 clusters of countries in terms of different marginal effects of growth determinants. The resulting finite mixture panel model outperforms a homogenous growth regression model for all countries, as well as country-specific growth regressions.

Our estimation results show that the structural differences between the countries in the two clusters are caused by different marginal effects of investment measures (gross domestic investment, and price of investment), openness measures (total trade as a percentage of GDP, and real exchange rate distortions), and government share of the economy. On the other hand, conditional on the covariates, the mean growth rates are not found to be significantly different for the two clusters of countries.

We compare the identified cluster memberships of the countries with conventional clustering variables used in the literature, that is, initial GDP levels, initial human capital measures, and initial openness measures. None of these variables are found to provide a clear relationship with the data-based cluster memberships. Furthermore, the clusters do not show a clear geographical division either.

The remainder of this paper is organized as follows. In Section 2 we discuss the panel finite mixture panel model which we use for endogenous clustering. We also discuss several important aspects of the empirical model specification procedure, as well as the algorithm for parameter estimation. In Section 3 we present the data, while we discuss the empirical results in Section 4. We conclude in Section 5.

2 Finite Mixture Panel Model

Our approach to handle parameter heterogeneity builds upon the finite mixture modeling approach developed by Paap, Franses, and van Dijk (2005). They propose a model in which all regressors are assumed to have different parameters across clusters. We extend their model in order to allow for a subset of regressors to have common marginal effects across clusters. This formulation allows us to use Likelihood Ratio (LR) tests to check for overparametrization, i.e. to test common versus heterogenous effects of regressors across clusters. In addition, if some regressors are found to have common effects across clusters, more efficient estimates can be obtained as incorporating this restriction into the model reduces the number of parameters to be estimated.

The growth rates of real GDP per capita for N countries are assumed to be a mixture of J distributions or clusters, each defined by a homogenous model. Let $s_i \in \{1, \ldots, J\}$ denote the cluster which country i belongs to, for $i = 1, \ldots, N$. We assume that s_i is unknown and has to be estimated from the data. A priori, there is a constant probability that country i belongs to cluster j. For $j \in \{1, \ldots, J\}$, this cluster membership probability is given by $p_j = \Pr[s_i = j]$, where $p_j \in (0, 1)$ and $\sum_{j=1}^{J} p_j = 1$ by definition.

Given J and s_i, we consider the following regression model for the growth rate of real GDP per capita $g_{i,t}$ of country $i = 1, \ldots, N$ in year $t = 1, \ldots, T$:

$$g_{i,t} = w'_{i,t}\gamma + x'_{i,t}\beta_{s_i} + z'_{i,t}\alpha_i + \varepsilon_{i,t}, \tag{1}$$

where $\varepsilon_{i,t} \sim NID\,(0, \sigma_i^2)$.

Unlike conventional growth equations, which mainly define models for cross-country data and fixed effects for certain groups of countries, (1) defines a panel data model with slope heterogeneity depending on three sets of regressors, that is, x, w and z. First, the regressors in the $k_w \times 1$ vector $w_{i,t}$ have the same marginal effects across both clusters and countries. Second, the regressors in the $k_x \times 1$ vector $x_{i,t}$ have different effects across clusters, but the same effects for all countries within a given cluster. Hence, the parameters associated with these variables specify the structural differences in the distribution of the dependent variable across clusters. Third, the variables in the $k_z \times 1$ vector $z_{i,t}$ have different marginal effects across countries even within the same cluster. The vectors $w_{i,t}$, $x_{i,t}$ and $z_{i,t}$ are said to contain the common variables, cluster-dependent variables, and country-specific variables, respectively.

At first sight, it seems that the slope heterogeneity in (1) is defined by the marginal effects of the regressors in the $x_{i,t}$ and $z_{i,t}$ vectors. However, it should be noted that the country-specific regressors in the vector $z_{i,t}$ in fact do not aim to capture such heterogeneity. Although growth determinants could possibly have different effects for all countries, the finite mixture model can capture such heterogeneities completely through the regressors in $x_{i,t}$, without the vector $z_{i,t}$, by taking the number of clusters J equal to the number of countries N. Instead, in the general model in (1) we include the vector $z_{i,t}$ to capture the cross-country error correlations in the growth regression. The way to implement this is to define a regressor in z that has the same values for all countries within a time period, i.e. $z_{i,t} = z_t$ for all $i = 1, \ldots, N$.

2.1 Model specification

There are two important issues when using the model in (1). First, the number of mixture components J has to be determined from the data in order to deal with parameter heterogeneity in a general way. Second, one has to classify the regressors into the three different types, that is, the vectors $w_{i,t}$, $x_{i,t}$ and $z_{i,t}$.

To determine J, standard tests are not applicable. It is well documented that in case of finite mixture models, the number of clusters cannot be selected using standard tests, due to the presence of unidentified nuisance parameters. For example, when testing the null hypothesis of J clusters against the alternative of $J+1$ clusters, the unrestricted log-likelihood function for such a test is not bounded under the null and, consequently, the asymptotic distribution of the LR statistic is not χ^2. The two most common ways to deal with this problem in the literature are to use parametric or non-parametric bootstraps (see e.g. Turner, 2000; Wedel, 2002, for discussion), or to rely upon information criteria. Examining several information criteria on simulated data, Jedidi *et al.* (1997) show that the consistent Akaike Information Criterion - CAIC (Bozdogan, 1987) and Bayesian Information Criterion - BIC (Schwarz, 1978) have the best performance in case of mixture models. Following their results, we use CAIC and BIC for determining the number of clusters. Therefore, the model parameters are first estimated for fixed J, and the information criteria for different values of J are compared to decide upon the appropriate number of clusters.

For a given value J we can use standard tests to classify the regressors into the $w_{i,t}$, $x_{i,t}$ and $z_{i,t}$ vectors. Given the data-based nature of the finite mixture modeling approach, we suggest to follow a data-driven procedure to define these vectors.

Given a particular choice of covariates to be included in the model, one possibility is to initialize the model in (1) by including all covariates in the country-specific covariate vector $z_{i,t}$, and then testing for common coefficients across countries. This would lead to the endogenous clustering approach followed by Hobijn and Franses

(2000). Note that this approach essentially means that we first estimate the model for $J = N$, and then try to reduce the number of clusters by imposing suitable parameter restrictions. This approach would require a substantial data set if the number of regressors is fairly large, as in our case. Furthermore, it is difficult to control for the overall size of the sequential testing procedure.

An alternative approach is to start from a homogenous linear model, and then test for different marginal effects of the regressors. In this case, all regressors are put in the vector $w_{i,t}$ initially, which is then tested against more general models with part of the regressors put in the vector(s) $x_{i,t}$ (or $z_{i,t}$). However, the choice of the cluster-specific regressors in x (or z) is not obvious, and as a result, all restricted models potentially have omitted variable bias in this case.

Given these considerations, we use a general-to-specific approach in terms of parameter heterogeneity. All covariates are initially assumed to be cluster-dependent and enter the $x_{i,t}$ vector (i.e. we start with an empty vector $w_{i,t}$ vector for all i and t), and the optimal number of clusters in this model is determined using the information criteria. In a second step, given the number of clusters we test for common marginal effects for each of the regressors separately. Using the test results we impose the appropriate parameter restrictions and we estimate a restricted model with part of the regressors moved from $x_{i,t}$ to $w_{i,t}$.

2.2 Parameter estimation

The parameters of the finite mixture panel model can be estimated using Maximum Likelihood (ML). Since we are dealing with a finite mixture model and cluster memberships of the individual countries are unknown, the Expectation Maximization (EM) method by Dempster *et al.* (1977) is a convenient way to maximize the likelihood function. To derive the steps of the EM algorithm, we first consider the complete data likelihood function, for which the cluster indicators s_i are assumed to be observed. The complete data likelihood function is given by

$$l(g,s;\theta) = \prod_{i=1}^{N} \prod_{j=1}^{J} \left(p_j \prod_{t=1}^{T} \frac{1}{\sigma_i} \phi \left(\frac{\varepsilon_{i,t}^{(j)}}{\sigma_i} \right) \right)^{I(s_i=j)}, \tag{2}$$

where $I(.)$ is the indicator function which takes the value 1 if the argument is true, and zero otherwise. $\phi(.)$ is the standard normal density function, and the cluster-specific error term is given by

$$\varepsilon_{i,t}^{(j)} = g_{i,t} - w_{i,t}'\gamma - x_{i,t}'\beta_j - z_{i,t}'\alpha_i. \tag{3}$$

The EM algorithm is an iterative algorithm which consists of two steps, that is, an expectation step followed by a maximization step. In the expectation step, the expected value of the complete data log-likelihood function with respect to the missing or unobserved data is computed. In the finite mixture model, the cluster indicators, s_i for $i = 1, ..., N$, are unobserved. Hence, in this case the expectation of the log of the complete data likelihood function (2) with respect to these latent variables (conditional on the observed variables) is given by

$$L(g;\theta) = \sum_{i=1}^{N} \sum_{j=1}^{J} p_{ij}^{*} \left(\ln(p_j) - \frac{T}{2} \ln \sigma_i^2 - \frac{T}{2} \ln 2\pi - \sum_{t=1}^{T} \frac{\left(\varepsilon_{i,t}^{(j)}\right)^2}{2\sigma_i^2} \right), \tag{4}$$

where the expected cluster probabilities p_{ij}^{*} are defined as follows:

$$p_{ij}^{*} = \frac{p_j \prod_{t=1}^{T} \frac{1}{\sigma_i} \phi\left(\frac{\varepsilon_{i,t}^{(j)}}{\sigma_i}\right)}{\sum_{l=1}^{J} p_l \prod_{t=1}^{T} \frac{1}{\sigma_i} \phi\left(\frac{\varepsilon_{i,t}^{(l)}}{\sigma_i}\right)}. \tag{5}$$

In the maximization step, the expected log-likelihood function in (4) is maximized with respect to the model parameters p_j and β_j for $j = 1, ..., J$, α_i and σ_i^2 for $i = 1, ..., N$, and γ. The first-order conditions for maximization are derived in Appendix B. The E- and M-steps are repeated until convergence. The resulting values of the parameters are the ML estimates.

The ML parameters can be used to estimate the value of s_i given the data, for $i = 1, \ldots, N$. This estimate is equal to the expected cluster membership probability (5) evaluated at the ML estimates. Hence, p^*_{ij} provides the posterior probability that country i belongs to cluster j. It can be seen from (4) that each observation is weighted according to these posterior probabilities in the objective function. Hence the estimated cluster memberships are not taken as fixed while estimating the regression parameters, unlike the exogenous clustering methods used in the growth literature. The uncertainty in the estimated cluster memberships is also taken into account in parameter estimation and inference.

3 Data

Our data set consists of annual observations for an unbalanced panel of 59 countries in Asia, Latin and Middle America and Africa covering the period 1971-2000. The countries are selected according to data availability, where we require observations to be available for at least half of the sample period. The list of included countries is given in Appendix A.

The regressors included in (1) cover variables that have traditionally been considered as important determinants of economic growth. Specifically, the explanatory variables we use are (i) human capital, measured by the logarithm of secondary school enrollment as a percentage of the population over 25 years; (ii) the annual growth rate of the population between 15 and 65 years; (iii) the logarithm of total trade as a percentage of GDP and real exchange rate distortions as proxies for openness measures; (iv) annual inflation as proxy for macroeconomic stability; (v) the government share of GDP in percent; (vi) the logarithm of the price of investment and Gross Domestic Investment (GDI) as a percentage of GDP.[1] The last variable is

[1]This choice of regressors is by no means exclusive. Some regressors used in several growth

not included in some studies for endogeneity reasons. We include this regressor but do make sure to employ endogeneity checks following the approach of Barro (1996).

The dependent variable is the annual growth rate of real GDP per capita, which is obtained from the Penn World Tables version 6.2 (PWT 6.2). The government share of GDP, price of investment and GDI variables are also taken from PWT 6.2. Real exchange rate distortions, trade percentage and inflation variables are obtained from the Global Development Network Growth Database, which in turn uses the World Development Indicators (WDI), and Global Development and Finance databases. For the labor force growth, we use the WDI database for population between 15-65 years. Secondary school enrollment percentages in the population over 25 years are taken from Barro and Lee (2000). Their educational data is available mostly for 5-year intervals, and we obtain annual observations by using spline interpolation.

We emphasize that we do not include any dummy variables or country-specific factors in this model. These variables are commonly employed in growth regressions to capture the heterogeneity in the mean growth rates. Instead, in our finite mixture approach, any heterogeneity in mean growth rates as well as in the marginal effects of regressors are completely determined by the data. We will however investigate if the endogenously determined clusters of countries correspond to, for example, regional dummies or country-specific factors.

4 Empirical Results

We estimate the finite mixture panel data model presented in Section 2 for the annual real GDP per capita growth rates of 59 countries over the period 1971-2000, including the growth determinants discussed in the previous section. For model specification we follow the general-to-specific approach outlined before. Hence, in terms of the

regressions such as population density or squared inflation are not included in the model as a result of data availability or the presence of high multicollinearity with the other regressors.

notation in Section 2, initially all regressors are assumed to have cluster-dependent marginal effects, and are included in the vector $x_{i,t}$. We refer to this specification, for which $w_{i,t}$ is empty, as the 'general model'. As discussed in Section 2, the variables $z_{i,t}$ can be used to capture any remaining cross-country correlation in the annual growth rates. Here we follow Paap, Franses, and van Dijk (2005), and include US real GDP per capita growth rate in $z_{i,t}$ for this purpose. As they note, this variable can be seen as representing the "world business cycle". Finally, the regressors are demeaned such that the intercepts correspond with average growth rates.

The first step in the analysis is to determine the number of clusters, J. For this purpose, we estimate the finite mixture model for 2 to 7 clusters,[2] as well as a linear model ($J = 1$) where the growth equation is homogenous for all countries. Finally, we also consider a model where all countries are analyzed separately rather than making any parameter homogeneity assumptions across countries. This last case, where the growth equation is different for all countries, corresponds to $J = 59$.

The results in Table 1 show that both BIC and CAIC indicate a clear preference for a model with $J = 2$ clusters. Note in particular that the finite mixture model is preferred over a homogenous growth rate equation for the included countries ($J = 1$). This result is in line with other studies on heterogeneity of growth determinants, such as Kalaitzidakis *et al.* (2001), Hansen (2000), and Cuaresma and Doppelhofer (2007). Furthermore, we see that the finite mixture model with 2 clusters also performs better than the country-specific growth regressions ($J = 59$) in terms of the information criteria.

Table 2 reports the parameter estimates for the finite mixture model with $J = 2$ clusters, along with the LR tests for the joint significance of the coefficients of a particular regressor in both clusters (4th column) and for equal marginal effects across

[2]The EM algorithm may converge to a local maximum. To prevent reporting local maximum results, we use 4000 different random starting cluster probabilities. For all considered models, the estimation results belonging to the highest log-likelihood value are reported.

clusters (5th column). Both the LR tests for joint significance and the individual t-statistics indicate that except for the population growth rate all variables have statistically significant coefficients at the 5% level in at least one of the clusters. Hence, apart from the population growth rate, we find that all included regressors are important determinants of economic growth.

The most interesting aspect of the model of course concerns the differences in the marginal effects of the regressors across clusters. Recall that the variables with distinct coefficients identify the structural differences between the countries in the two clusters. Based on the p-values of the LR tests for common marginal effects reported in the final column of Table 2, we find that the parameters differ significantly across clusters for investment, real exchange rate distortions, trade percentage, government share and investment price.

Several structural differences in growth patterns between the countries in the two clusters are apparent from the estimation results. First, growth is much more sensitive to investment for countries in cluster 2 compared to those in cluster 1. Although GDI has a positive effect on growth in both clusters, the effect is almost twice as large in cluster 2. Furthermore, we do not find a significant coefficient for the price of investment in cluster 1, whereas this variable has a significant positive effect on growth for countries in cluster 2.

The second difference between the clusters is in terms of the marginal effects of openness variables. For both openness measures, that is, total trade percentage and real exchange rate distortions, the marginal effects clearly differ across the clusters. For trade, we find significantly positive and negative effects on growth for the first and second clusters, respectively. Hence, trade openness is beneficial for economic growth in cluster 1 countries, but it depresses economic growth for cluster 2 countries. For the exchange rate distortions on the other hand, the marginal effect on growth is not significant for cluster 1, while we find a significantly negative coefficient for the countries in cluster 2.

Third, fiscal policy, measured by the government share in GDP, also has different effects across clusters. For the countries in cluster 1, an increase in the government share in the economy has a significantly negative effect on growth, indicating that the government sector in these countries is relatively less efficient compared to the private sector. For cluster 2 on the other hand, government share does not have a significant effect on growth.

The human capital variable, that is, secondary school enrollment rates in the population over 25, has a negative and significant coefficient for both clusters. This result is rather surprising since we would expect schooling in the working age population to stimulate growth through human capital accumulation[3].

Finally, it is interesting to point out that, although the estimated intercept in Table 2 is higher for cluster 1, the difference with the mean growth rate in cluster 2 is not statistically significant. This result is quite different from conventional growth studies, which only allow the mean growth rate to vary across countries but restrict the marginal effects of other regressors to be the same. Hence, the significant differences in mean growth rates reported in such studies may in fact be due to the different marginal effects of growth determinants, as uncovered by our finite mixture model.

Figure 1 and Table 3 show the cluster memberships for the countries included in our data set based on the posterior cluster membership probabilities. Here, country i is said to belong to cluster j if its estimated posterior probability of being in this cluster based on (5) is greater than 0.5. The figure and table show that the division based on posterior cluster membership probabilities does not match with regional specifications, especially for Africa and Latin and Middle America. Most Asian

[3]The correlation between the human capital and real GDP growth rate is also negative when these two variables are analyzed in a separate regression, that is, when real GDP per capita growth rates are regressed on a constant and secondary school enrollment rates.

countries are in cluster 2, for which returns to investment are relatively higher, and monetary instability measured by annual inflation has a negative effect on economic growth.

A further comparison of the clustering implied by the finite mixture model and the regional segmentation often applied in the literature is given in Table 4, showing the average posterior cluster probabilities for the total sample, as well as for the countries in the three geographical regions that are represented in our sample. The average probabilities per region are calculated from (5) averaged over the countries in each region. Asian countries have the highest probability to belong to the second cluster, while the reverse holds for the countries in Latin and Middle America.[4] Furthermore, there is no clear pattern for the countries in sub-Saharan Africa, as their average probability to belong to cluster 2 is close to 50% in Table 4. We conclude that there are parameter heterogeneities across the countries considered, but these heterogeneities do not match with conventional regional divisions.

Next, we consider the possibility to make the model more parsimonious by imposing the restriction of common marginal effects across clusters for some regressors. The results of the individual LR tests on common marginal effects displayed in the final column of Table 2 suggests that this restriction may be imposed for school enrollment, population growth and inflation. The joint LR test for common marginal effects of all three regressors equals 5.32 with a p-value of 0.15. Hence, we do not reject common marginal effects for these regressors jointly.

Based on these results, we estimate a restricted model where school enrollment, population growth and annual inflation have the same marginal effects for all countries considered. Using the notation in Section 2, we now put these variables in the $w_{i,t}$ vector. The parameter estimates for this 'restricted model' are given in Table 5.

[4] From the countries considered, one can argue that the performance of Japan over the time span considered is rather different from the remaining countries. For this reason we also estimated the models excluding Japan from the sample. The general results in terms of the optimal number of clusters, the signs and the significance of the explanatory variables remain the same.

The results in terms of the cluster-dependent variables are in line with the general, unrestricted model: The estimated mean growth rate is larger for the countries in cluster 1 and returns to investment are lower. Countries in cluster 2 are negatively affected by real exchange rate distortions, while this variable does not have a significant effect for countries in cluster 1. Similar to previous results, cluster 1 is characterized by a negative effect of government size in the economy on growth.

Next, we consider the regressors with homogenous effects in the restricted regression displayed in the final columns of Table 5. The common effect of schooling is negative and significant. Similar to the previous t-tests and LR tests, we do not find a significant effect of population growth. In terms of monetary policy stability, when inflation is analyzed as a common regressor, the marginal effect on growth is negligible for all countries in the data set.

Figure 2 shows the country clusters based on the posterior cluster membership probabilities for the restricted model. Although the parameter estimates for the clusters are similar, five countries, namely Gambia, Haiti, Nepal, Papua New Guinea and Zimbabwe, are in different clusters compared to the general model. Note that for all these countries except Zimbabwe, the posterior probabilities reported in Table C.1 are relatively close to 0.5. Hence the cluster membership probabilities for these countries are not very informative.

Table 6 reports the average cluster probabilities for geographical groups for the restricted model. The results in terms of the average regional patterns hold in the restricted model as well: Although Asian countries have the highest probability to belong to cluster 2, the estimated clusters do not match with geographical divisions.

4.1 Robustness checks

Starting from the general model with $J = 2$ clusters, we perform three additional checks to examine the robustness of our results. First, we test for endogeneity of investment. Second, we check whether there are regional patterns that our results cannot cover. Finally, we compare the estimated clusters with the threshold variables used in the literature in order to see whether the finite mixture model is just an approximation for a model with a threshold specification on the regressors.

For the endogeneity of investment, we follow the approach of Barro (1996). He proposes a simple comparison to check for reverse causality using the lagged value of investment as a regressor. If the model with lagged investment does not lead to significant parameter estimates, we should conclude that the causality is from growth to investment, and there is an endogeneity problem in the estimation of the finite mixture model. Table 7 presents the estimation results with 2 clusters where lagged value of Gross Domestic Investment is used as a regressor instead of the contemporaneous value.

Table 7 shows that the marginal effect of the lagged investment variable is positive and significant in both clusters. Hence the analysis does not indicate an endogeneity problem in investment.

In order to check whether there are regional patterns that our results cannot cover, we estimate a model including the conventional regional dummy variables in the literature. Specifically, we estimate the model including dummy variables for the East Asian and sub-Saharan African countries. Parameter estimates for this model are given in Table 8. Note that a significant coefficient for the dummy variables would indicate that there are regional patterns in growth that the finite mixture model with 2 clusters cannot uncover. The results in Table 8 show that both dummy variables do not have a significant effect on growth. Therefore, we do not find any indications for unexplained regional patterns in terms of sub-Saharan Africa or East Asia.

Finally, we examine the relation of the endogenous clustering results with some threshold variables. The literature using exogenous clustering for growth rates mainly considers three threshold variables for heterogeneity in growth rates, namely initial GDP per capita, openness and schooling measures, see e.g. Durlauf and Johnson (1995) and Cuaresma and Doppelhofer (2007). Figure 3 shows scatter diagrams of the estimated cluster probabilities and these threshold variables for the models with two clusters. An accurate threshold variable would imply that the cluster probabilities below a certain threshold are smaller than 0.5 while cluster probabilities above the threshold are larger than 0.5, or vice versa.[5]

The scatter diagrams do not show a clear relationship between the threshold variables and the cluster probabilities. Hence, the finite mixture model is not just an approximation for a model with threshold variables. In other words, the thresholds of initial GDP per capita, initial openness or initial schooling do not capture country heterogeneities accurately for this data set.

We conclude that within the data set we have considered, there are two groups of countries with different marginal effects of the variables affecting growth. The estimated country classification is different from conventional segmentations based on geographical location or threshold variables. The resulting model does not seem to suffer from an endogeneity problem in terms of investment or omitted parameter heterogeneities.

5 Conclusion

Using a finite mixture model and endogenous clustering, we analyze the structural differences in economic growth rates for 59 countries in Latin and Middle America, Asia and Africa for the period 1971-2000. The countries are not grouped beforehand according to, for example, geographical location or the (relative) value of certain covariates. The structural differences and the country groups are rather determined

[5]Initial openness measure is the trade percentage at the beginning of the sample period, and for initial schooling we use secondary school enrollment rates in the population over 25.

endogenously. The model allows for heterogeneities in the marginal effects of all considered variables affecting growth.

The analysis leads to two important conclusions. First, in line with many previous studies, the results indicate structural differences in growth patterns across countries. The included countries are optimally divided into two groups according to these structural differences. The optimal groups do not match with the conventional regional classifications in the literature. For all three regions that are distinguished, we find a substantial number of countries in both clusters. In particular, we find evidence against treating African countries as a homogenous group which is different from the rest of the developing world. Moreover, we find that threshold variables such as initial GDP levels, human capital levels, or openness measures, also do not explain the heterogeneities for the included countries accurately.

Second, the results show that the structural differences between the countries are in terms of the marginal effects of several regressors: investment (both gross domestic investment and the price of investment), openness measures (total trade as a percentage of GDP, and real exchange rate distortions), and the government share in GDP all have heterogenous effects between the country clusters. In addition, we do not find significant differences in the mean growth rate across clusters.

In our future work, we intend to account for model uncertainty in economic growth while using this systematic way to deal with parameter heterogeneity. Specifically, we aim to investigate the model uncertainties without assigning a priori groups of countries with homogenous growth structures.

Appendix A List of Included Countries

Africa: Algeria, Botswana, Cameroon, Central African Rep., Egypt, Gambia, Ghana, Kenya, Liberia, Lesotho, Malawi, Mauritius, Niger, Rwanda, Senegal, Sierra Leone, South Africa, Sudan, Swaziland, Togo, Uganda, Zimbabwe.

Latin and Middle America: Argentina, Barbados, Bolivia, Brazil, Chile, Colombia, Costa Rica, Dominican Republic, Ecuador, El Salvador, Guatemala, Haiti, Honduras, Jamaica, Mexico, Nicaragua, Paraguay, Peru, Trinidad&Tobago, Uruguay, Venezuela.

Asia:[6] India, Indonesia, Iran, Israel, Japan, Jordan, Korea Rep., Malaysia, Nepal, Pakistan, Philippines, Papua New Guinea, Sri Lanka, Syria, Thailand, Turkey.

[6]This group consists of Middle Eastern and Asian countries. We refer to this group as 'Asia' in the paper.

Appendix B EM Algorithm

As starting point of the algorithm we take the complete data likelihood function (2). Hence, the complete data log-likelihood function is

$$L(g, s; \theta) = \sum_{i=1}^{N} \sum_{j=1}^{J} I(s_i = j) \left(\ln(p_j) + \sum_{t=1}^{T} \ln \left(\frac{1}{\sigma_i} \phi \left(\frac{\varepsilon_{i,t}^{(j)}}{\sigma_i} \right) \right) \right). \tag{B.1}$$

The conditional (on the data and parameters) probability for country i to be included in cluster j is given by the ratio of country i's likelihood contributions to the J segments, that is,

$$p_{ij}^* = \frac{p_j \prod_{t=1}^{T} \frac{1}{\sigma_i} \phi \left(\frac{\varepsilon_{i,t}^{(j)}}{\sigma_i} \right)}{\sum_{l=1}^{J} p_l \prod_{t=1}^{T} \frac{1}{\sigma_i} \phi \left(\frac{\varepsilon_{i,t}^{(l)}}{\sigma_i} \right)} \qquad \text{for } j = 1, ..., J. \tag{B.2}$$

Hence, the expected value of the complete data log-likelihood function [E-step] is

$$L(g; \theta) = \sum_{i=1}^{N} \sum_{j=1}^{J} p_{ij}^* \left(\ln(p_j) - \frac{T}{2} \ln \sigma_i^2 - \frac{T}{2} \ln 2\pi - \sum_{t=1}^{T} \frac{\left(\varepsilon_{i,t}^{(j)} \right)^2}{2\sigma_i^2} \right). \tag{B.3}$$

The first-order conditions for maximizing (B.3) [M-step] are given by

$$\frac{\partial L(g; \theta)}{\partial \beta_j} = \sum_{i=1}^{N} \frac{p_{ij}^*}{\sigma_i^2} \sum_{t=1}^{T} x_{i,t} \varepsilon_{i,t}^{(j)} = 0 \qquad \text{for } j = 1, ..., J, \tag{B.4}$$

$$\frac{\partial L(g; \theta)}{\partial \alpha_i} = \sum_{j=1}^{J} \frac{p_{ij}^*}{\sigma_i^2} \sum_{t=1}^{T} z_{i,t} \varepsilon_{i,t}^{(j)} = 0 \qquad \text{for } i = 1, ..., N, \tag{B.5}$$

$$\frac{\partial L(g; \theta)}{\partial \gamma} = \sum_{i=1}^{N} \sum_{j=1}^{J} \frac{p_{ij}^*}{\sigma_i^2} \sum_{t=1}^{T} w_{i,t} \varepsilon_{i,t}^{(j)} = 0 \tag{B.6}$$

$$\frac{\partial L(g; \theta)}{\partial \sigma_i^2} = \sum_{j=1}^{J} \frac{p_{ij}^*}{\sigma_i^2} \left(-\frac{T}{2\sigma_i^2} + \sum_{t=1}^{T} \frac{\left(\varepsilon_{i,t}^{(j)} \right)^2}{2\sigma_i^4} \right) = 0 \qquad \text{for } i = 1, ..., N. \tag{B.7}$$

The solution to these first-order conditions provides an update of the parameter estimates. The cluster membership probabilities are updated using

$$p_j = \frac{1}{N} \sum_{i=1}^{N} p^*_{ij}, \tag{B.8}$$

The E- and M-step are repeated until convergence is achieved. The resulting parameter values are equal to the ML estimates.

Appendix C Posterior Cluster Membership Probabilities

Table C.1: Posterior cluster membership probabilities for the model in Table 2

Cluster 1 Countries

Country	p^*_{i1}	p^*_{i2}	Country	p^*_{i1}	p^*_{i2}
Algeria	0.93	0.07	Jamaica	0.99	0.01
Barbados	1.00	0.00	Japan	1.00	0.00
Bolivia	1.00	0.00	Korea Republic of	0.99	0.01
Botswana	0.98	0.02	Lesotho	0.85	0.15
Brazil	1.00	0.00	Mauritius	1.00	0.00
Cameroon	0.70	0.30	Nicaragua	1.00	0.00
Colombia	1.00	0.00	Peru	0.98	0.02
Costa Rica	0.91	0.09	Rwanda	0.88	0.12
Ecuador	0.85	0.15	Senegal	1.00	0.00
Egypt	1.00	0.00	Sri Lanka	0.99	0.01
El Salvador	1.00	0.00	Swaziland	1.00	0.00
Gambia, The	0.54	0.46	Syria	1.00	0.00
Guatemala	1.00	0.00	Togo	0.75	0.25
Haiti	0.55	0.45	Trinidad &Tobago	0.99	0.01
Iran	1.00	0.00	Venezuela	0.95	0.05

Cluster 2 Countries

Country	p^*_{i1}	p^*_{i2}	Country	p^*_{i1}	p^*_{i2}
Argentina	0.00	1.00	Nepal	0.00	1.00
Central African Republic	0.00	1.00	Niger	0.09	0.91
Chile	0.03	0.97	Pakistan	0.02	0.98
Dominican Republic	0.01	0.99	Papua New Guinea	0.48	0.52
Ghana	0.03	0.97	Paraguay	0.00	1.00
Honduras	0.00	1.00	Philippines	0.00	1.00
India	0.00	1.00	Sierra Leone	0.00	1.00
Indonesia	0.00	1.00	South Africa	0.00	1.00
Israel	0.00	1.00	Sudan	0.04	0.96
Jordan	0.00	1.00	Thailand	0.00	1.00
Kenya	0.00	1.00	Turkey	0.00	1.00
Liberia	0.29	0.71	Uganda	0.00	1.00
Malawi	0.00	1.00	Uruguay	0.14	0.86
Malaysia	0.01	0.99	Zimbabwe	0.01	0.99
Mexico	0.00	1.00			

Note: The table presents posterior cluster membership probabilities for the finite mixture model (1) with $J = 2$ clusters, estimated for annual real GDP per capita growth rates for 59 countries over the period 1971-2000. All regressors are allowed to have different marginal effects across clusters. Posterior cluster membership probabilities are given by (5) evaluated at the ML estimates.

Table C.2: Posterior cluster membership probabilities for the model in Table 5

Cluster 1 Countries

Country	p_{i1}^*	p_{i2}^*	Country	p_{i1}^*	p_{i2}^*
Algeria	0.96	0.04	Lesotho	0.94	0.06
Barbados	1.00	0.00	Mauritius	1.00	0.00
Bolivia	0.64	0.36	Nepal	0.64	0.36
Botswana	0.96	0.04	Nicaragua	1.00	0.00
Brazil	1.00	0.00	Papua New Guinea	0.61	0.39
Cameroon	0.83	0.17	Peru	0.98	0.02
Colombia	1.00	0.00	Rwanda	0.97	0.03
Costa Rica	0.69	0.31	Senegal	1.00	0.00
Ecuador	0.71	0.29	Sri Lanka	0.98	0.02
Egypt	1.00	0.00	Swaziland	1.00	0.00
El Salvador	1.00	0.00	Syria	1.00	0.00
Guatemala	1.00	0.00	Togo	0.95	0.05
Iran	1.00	0.00	Trinidad &Tobago	0.98	0.02
Jamaica	0.99	0.01	Venezuela	0.97	0.03
Japan	1.00	0.00	Zimbabwe	0.94	0.06
Korea Republic of	0.99	0.01			

Cluster 2 Countries

Country	p_{i1}^*	p_{i2}^*	Country	p_{i1}^*	p_{i2}^*
Argentina	0.00	1.00	Malawi	0.00	1.00
Central African Republic	0.00	1.00	Malaysia	0.07	0.93
Chile	0.05	0.95	Mexico	0.00	1.00
Dominican Republic	0.02	0.98	Niger	0.00	1.00
Gambia, The	0.49	0.51	Pakistan	0.01	0.99
Ghana	0.06	0.94	Paraguay	0.00	1.00
Haiti	0.43	0.57	Philippines	0.00	1.00
Honduras	0.01	0.99	Sierra Leone	0.00	1.00
India	0.00	1.00	South Africa	0.00	1.00
Indonesia	0.00	1.00	Sudan	0.00	1.00
Israel	0.00	1.00	Thailand	0.00	1.00
Jordan	0.00	1.00	Turkey	0.00	1.00
Kenya	0.00	1.00	Uganda	0.00	1.00
Liberia	0.42	0.58	Uruguay	0.45	0.55

Note: The table presents posterior cluster membership probabilities for the finite mixture model (1) with $J = 2$ clusters, estimated for annual real GDP per capita growth rates for 59 countries over the period 1971-2000. Secondary school enrollment, population growth rate and inflation are assumed to have the same marginal effects across clusters, while the rest of the explanatory variables have different marginal effects across clusters. Posterior cluster membership probabilities are given by (5) evaluated at the ML estimates.

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Tables and Figures

Table 1: Information criteria for different number of clusters

J	1	2	3	4	5	6	7	59
Based on number of cross-sections (59 observations)								
BIC	−65.67	−66.63*	−66.50	−66.36	−66.18	−65.88	−65.50	−44.26
CAIC	−63.52	−64.30*	−64.00	−63.70	−63.35	−62.89	−62.33	−33.26
Based on total number of observations (1482 observations)								
BIC	−2.34	−2.35*	−2.33	−2.30	−2.27	−2.24	−2.20	−0.35
CAIC	−2.25	−2.26*	−2.23	−2.19	−2.16	−2.21	−2.07	0.09

Note: The table presents values of the Bayesian Information Criterion (BIC) and consistent Akaike Information Criterion (CAIC) for the finite mixture model (1) with J clusters, estimated for annual real GDP per capita growth rates for 59 countries over the period 1971-2000. For simplification, information criteria are divided by the number of observations in all cases. The model with smallest information criteria is to be preferred. An asterisk indicates the minimum value of the information criteria.

Table 2: Estimation results for the general finite mixture model with $J = 2$ clusters

Variable	Cluster 1	Cluster 2	p-value[a] (joint significance)	p-value[b] (common marg. effects)
intercept	4.211**	3.164**	0.000	0.322
	(0.667)	(0.687)		
investment	2.820**	5.470**	0.000	0.004
	(0.640)	(0.670)		
school enr.	−2.929**	−1.684**	0.000	0.104
	(0.508)	(0.431)		
pop. growth	29.028	−7.450	0.193	0.382
	(21.247)	(35.103)		
RER distor.	0.000	−0.004**	0.007	0.000
	(0.000)	(0.001)		
trade%	3.846**	−1.435**	0.000	0.000
	(0.742)	(0.653)		
inflation	0.000	−0.002**	0.035	0.111
	(0.000)	(0.001)		
govt. share	−6.314**	1.710*	0.000	0.000
	(0.903)	(0.999)		
invest. price	−1.168	3.281**	0.019	0.000
	(0.739)	(0.796)		

Note: The table shows parameter estimates with standard errors in parentheses for the finite mixture model (1) with $J = 2$ clusters, estimated for annual real GDP per capita growth rates for 59 countries over the period 1971-2000. All regressors are allowed to have different marginal effects across clusters. The regressors are demeaned such that the intercepts correspond with average growth rates. Parameter estimates and standard errors are multiplied by 100. * and ** denote significance at 10% and 5% levels, respectively.

[a] Asymptotic p-values for the LR tests for the joint significance of the parameters in both segments.

[b] Asymptotic p-values for the LR tests for equal marginal effects in both clusters.

Table 3: Posterior clustering for the general finite mixture model with $J = 2$ clusters

	Africa
Cluster 1	Algeria, Botswana, Cameroon, Egypt, Gambia, Lesotho, Mauritius, Rwanda, Senegal, Swaziland, Togo
Cluster 2	Central African Rep., Ghana, Kenya, Liberia, Malawi, Niger, Sierra Leone, South Africa, Sudan, Uganda, Zimbabwe
	Latin and Middle America
Cluster 1	Barbados, Bolivia, Brazil, Colombia, Costa Rica, Ecuador, El Salvador, Guatemala, Haiti, Jamaica, Nicaragua, Peru, Trinidad&Tobago, Venezuela
Cluster 2	Argentina, Chile, Dominican Rep., Honduras, Mexico, Paraguay, Uruguay
	Asia
Cluster 1	Iran, Japan, Korea Rep., Sri Lanka, Syria
Cluster 2	India, Indonesia, Israel, Jordan, Malaysia, Nepal, Pakistan, Philippines, Papua New Guinea, Thailand, Turkey

Note: The table presents posterior clustering for the finite mixture model (1) with $J = 2$ clusters, estimated for annual real GDP per capita growth rates for 59 countries over the period 1971-2000. All regressors are allowed to have different marginal effects across clusters. The clustering is based on posterior cluster membership probabilities shown in Table C.1. Each country is assigned to the cluster with the highest posterior probability.

Table 4: Average posterior cluster probabilities per region for the general model

	Cluster probabilities	
Sample	cluster 1	cluster 2
All countries	0.49	0.51
	(0.08)	
Africa	0.46	0.54
Asia	0.36	0.64
Latin and Middle America	0.64	0.36
Sub-Saharan Africa	0.41	0.59

Note: The table presents posterior clustering for the finite mixture model (1) with $J = 2$ clusters, estimated for annual real GDP per capita growth rates for 59 countries over the period 1971-2000. All regressors are allowed to have different marginal effects across clusters. The average cluster probabilities per region are calculated using the posterior cluster membership probabilities shown in Table C.1. The standard error for cluster 1 probability is shown in parentheses.

Table 5: Estimation results for the restricted model with $J = 2$ clusters

Cluster dependent variables			*Cluster independent variables*	
Variable	Coefficient Estimates Cluster 1	Coefficient Estimates Cluster 2	Variable	Coefficient Estimate
intercept	3.688 *	3.642*	school enr.	-2.379*
	(0.555)	(0.595)		(0.368)
investment	2.419*	5.745*	pop. growth	19.574
	(0.604)	(0.693)		(16.958)
RER distor.	0.000	-0.004*	inflation	0.000
	(0.000)	(0.001)		(0.000)
trade%	3.575*	-1.225*		
	(0.692)	(0.617)		
govt. share	-6.277*	1.721**		
	(0.900)	(1.053)		
invest. price	-1.222**	3.630*		
	(0.627)	(0.855)		

Note: The table shows parameter estimates with standard errors in parentheses for the finite mixture model (1) with $J = 2$ clusters, estimated for annual real GDP per capita growth rates for 59 countries over the period 1971-2000. Secondary school enrollment, population growth rate and inflation are imposed to have the same marginal effects across clusters. All regressors are demeaned prior to analysis. Parameter estimates and standard errors are multiplied by 100. * and ** denote significance at 5% and 10% levels, respectively.

Table 6: Average cluster membership probabilities per region for the restricted model

Sample	*Cluster probabilities* cluster 1	cluster 2
All countries	0.47	0.53
	(0.08)	
Africa	0.52	0.48
Asia	0.41	0.59
Latin and Middle America	0.62	0.38
Sub-Saharan Africa	0.48	0.52

Note: The table presents posterior clustering for the finite mixture model (1) with $J = 2$ clusters, estimated for annual real GDP per capita growth rates for 59 countries over the period 1971-2000. Secondary school enrollment, population growth rate and inflation are assumed to have the same marginal effects across clusters. The average cluster probabilities per region are calculated using the posterior cluster membership probabilities shown in Table C.2. Each country is assigned to the cluster with the highest posterior probability. The standard error for cluster 1 probability is shown in parentheses.

Table 7: Estimation results for the model containing lagged investment

Variable	Coefficient Estimates		Variable	Coefficient Estimates	
	Cluster 1	Cluster 2		Cluster 1	Cluster 2
intercept	3.438	2.575	trade%	8.113	-0.898
	(0.718)	(0.569)		(0.999)	(0.566)
investment_{-1}	1.898*	2.013*	inflation	0.000	-0.002
	(0.728)	(0.561)		(0.000)	(0.001)
school enr.	-4.721	-1.197	govt. share	-6.368	-0.228
	(0.607)	(0.435)		(0.181)	(0.916)
pop. growth	-73.327	64.050	invest. price	1.021	0.623
	(34.914)	(19.020)		(0.880)	(0.643)
RER distor.	0.000	-0.004			
	(0.000)	(0.001)			

Note: The table shows parameter estimates with standard errors in parentheses for the finite mixture model (1) with $J = 2$ clusters, estimated for annual real GDP per capita growth rates for 59 countries over the period 1971-2000. Parameter estimates and standard errors (in parentheses) are multiplied by 100. The Gross Domestic Investment value in the previous period is denoted by investment_{-1}. * indicates significance at 5% level for lagged investment.

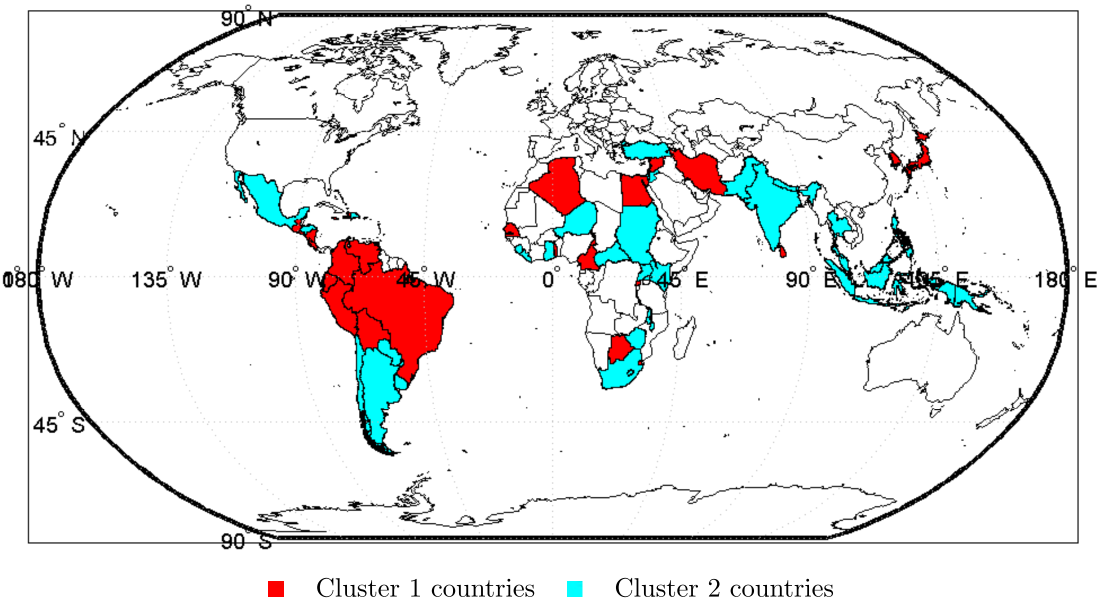
Table 8: Estimation results for the model containing regional dummies

		Cluster dependent explanatory variables			
Variable	Cluster 1	Cluster 2	Variable	Cluster 1	Cluster 2
intercept	4.357	3.557	trade%	3.994	-1.284
	(0.684)	(0.769)		(0.779)	(0.657)
investment	2.827	5.323	inflation	0.000	-0.002
	(0.647)	(0.728)		(0.000)	(0.001)
school enr.	-3.020	-1.691	govt. share	-6.370	1.512
	(0.532)	(0.427)		(0.906)	(1.035)
pop. growth	27.355	-4.700	invest. price	-1.123	3.366
	(21.045)	(35.308)		(0.746)	(0.783)
RER distor.	0.000	-0.004			
	(0.000)	(0.001)			

	Cluster independent explanatory variables
Variable	Coefficient estimate
East Asia dummy	-0.676
	(1.282)
Sub-Saharan Africa dummy	-0.747
	(1.082)

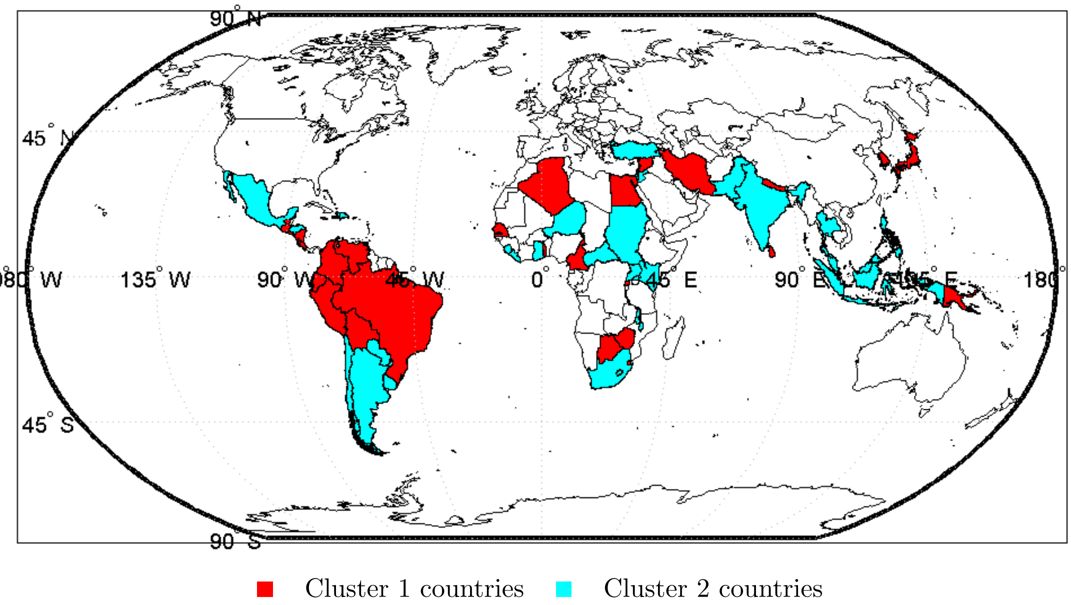
Note: The table shows parameter estimates with standard errors in parentheses for the finite mixture model (1) with $J = 2$ clusters, estimated for annual real GDP per capita growth rates for 59 countries over the period 1971-2000. Regional dummy variables for Sub-Saharan Africa and East Asia are added as cluster-independent regressors. Parameter estimates and standard errors (in parentheses) are multiplied by 100.

Figure 1: Posterior cluster memberships for the general model



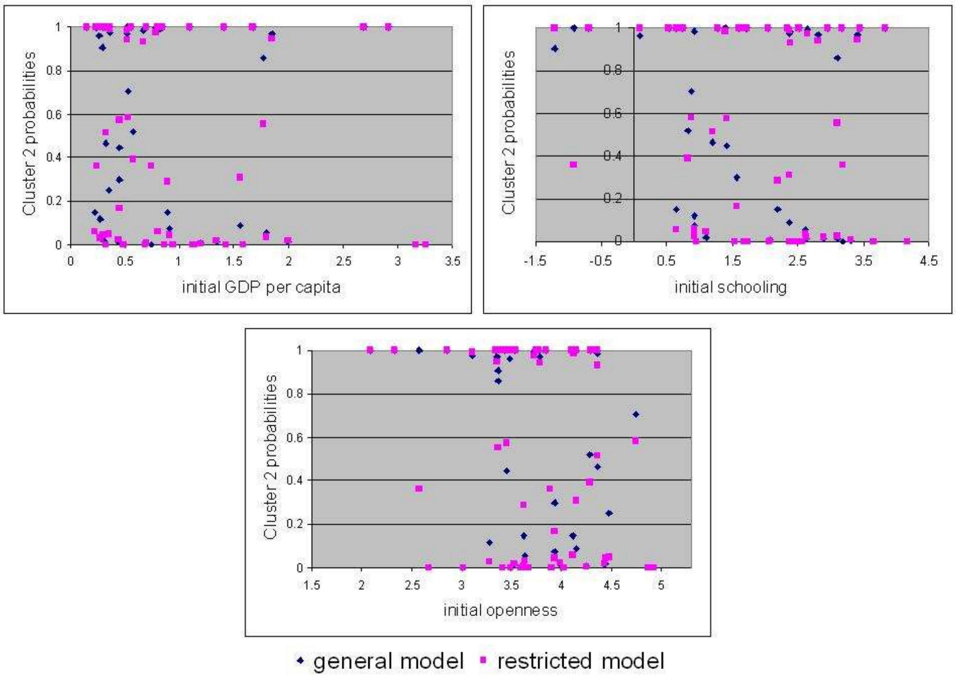
Note: The figure shows posterior cluster membership in the finite mixture model (1) with $J = 2$ clusters, estimated for annual real GDP per capita growth rates over the period 1971-2000. All regressors are allowed to have different marginal effects across clusters. Posterior cluster membership probabilities are given in Table C.1. Each country is assigned to the cluster with the highest posterior probability.

Figure 2: Posterior cluster memberships for the restricted model



Note: The figure shows posterior cluster membership in the finite mixture model (1) with $J = 2$ clusters, estimated for annual real GDP per capita growth rates over the period 1971-2000. Secondary school enrollment, population growth rate and inflation are assumed to have the same marginal effects across clusters, while the rest of the explanatory variables have different marginal effects across clusters. Posterior cluster membership probabilities are given in Table C.2. Each country is assigned to the cluster with the highest posterior probability.

Figure 3: Comparisons of cluster probabilities with threshold variables



Note: The figures show cluster 2 probabilities for the general and restricted models on the y-axes against the threshold variables on the x-axes. All threshold variables are demeaned, and initial schooling measures are in natural logarithms.