Do all countries follow the same growth process?

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Abstract

We estimate a finite mixture model in which countries are sorted into groups based on the similarity of the conditional distributions of their growth rates. We strongly reject the hypothesis that all countries follow a common growth process in favor of a model in which there are two classes of countries, each with its own distinct growth process. Group membership does not conform to the usual categories used to control for parameter heterogeneity such as region or income. However, we find strong evidence that one country characteristic that helps to sort countries into different regimes is the quality of institutions, specifically, the degree of law and order. Once institutional features of the economy are controlled for, we find no evidence that geographic characteristics play a role in determining the country groupings.

JEL Codes: O11, O17

Key words: finite mixture models, multiple equilibria, institutional quality

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1 Introduction

Is there a universal growth model, a single set of equations that govern the evolution of per capita income in every country or a majority of countries? And if not, is it possible to group countries in such a way that, within each group, we are able to draw inferences about their common growth experience? Or must we assume that each country's growth experience is fundamentally idiosyncratic, a position Hausmann, Rodrik and Velasco (2005:1) say results in an "attitude of nihilism" regarding our ability to understand economic growth? As these questions suggest, addressing the heterogeneity of country growth processes is of fundamental importance to the study of economic growth.

While most growth economists would agree that heterogeneity is an important consideration in empirical work, the most common methods for addressing heterogeneous growth are unsatisfactory. For example, the practice of including regional dummy variables or country fixed effects when panel data are available controls for differences in average growth rates, but it does not allow for differences in the marginal effect of the regressors. An alternative is to identify groups of countries for which the growth process is assumed to be similar, for example, developed and developing country groups, but this approach requires we choose an a priori income threshold and it may still result in groups with countries that follow very different growth processes. This latter concern appears to underlie the further partition of developing countries into regional subgroups such as African or Latin American countries.

In contrast to these somewhat ad hoc approaches, we employ a data-driven methodology to estimate multiple growth processes. We estimate a finite mixture model in which countries are sorted into groups based on the similarity of the conditional distributions of their growth rates. We model the distribution of growth rates as a function of variables identified as proximate determinants of growth: initial income, the rate of investment in physical capital, human capital, and the population growth rate. We also extend our analysis to use variables that describe institutional and geographic factors to improve the classification of countries into the different growth regimes.

Our results are as follows. First, we strongly reject the hypothesis that the countries in our sample follow a common growth process in favor of a model in which there are two distinct growth processes. Moreover, our parameter estimates differ significantly both across groups and from estimates found in a standard growth regression that assumes only one class. Second, we show that classification into the different growth regimes does not depend solely on categories such as income and region. Therefore, finite mixture regression modeling can improve upon the standard treatment of dividing countries by income level because it allows for parameter heterogeneity among countries with similar incomes. Finally, we show that institutional factors play a clear role in predicting membership in the country groups, but we find no evidence that geographic characteristics help to explain the country groupings. For growth empirics, our results suggest a middle ground to the two extremes mentioned at the start of the paper. All countries do not follow the same growth process, but neither is each country's growth process entirely unique. Our analysis shows that countries can be grouped in a meaningful way.

Our work is related to that of other researchers who have examined the heterogeneity of the growth process with increasing methodological sophistication. In a seminal paper in this literature, Durlauf and Johnson (1995) apply regression tree analysis to identify country groupings. These authors use output per capita and adult literacy rates to identify countries with common growth processes. Papageorgiou (2002) extends the work of Durlauf and Johnson (1995) by also exploring whether or not trade can be used as a threshold variable. More recently, Canova (2004) and Sirimaneetham and Temple (2006) have explored the existence of multiple growth regimes. Sirimaneetham and Temple (2006) use principal components analysis to generate an index of policy quality, sort economies into groups based on the value of the index, and then explore whether average growth rates vary across groups. Canova (2004) draws on Bayesian ideas to examine income levels in Europe. His technique allows him to explore alternative means of ordering countries to form groups and he finds that using initial income as a splitting variable generates four groups of countries. Our research shares the same motivation of these papers but our methodology complements and advances the existing literature. Contrary to Durlauf and Johnson (1995), Papageorgiou (2002), Canova (2004), and Sirimaneetham and Temple (2006), we assign countries to growth regimes based on the conditional distribution of the growth rate itself rather than predetermined factors. Our method also has the advantage of assuming a class or regime structure in which the regimes are discrete and unordered in the usual sense (i.e., the regimes are *different*, not necessarily better or faster growing).

Bloom, Canning, and Sevilla (2003) use methods more similar to ours, finding evidence that a model with two income regimes is statistically superior to a model with one regime. These authors also argue that geographical variables determine the likelihood that a country is assigned to any of the two regimes. However, unlike our work which focuses on the conditional distribution of growth rates, Bloom et al. focus on the unconditional distribution of the level of income and do not consider the possibility of more than two regimes. Like Bloom et al., we also explore the role of geography in determining the class or regime to which a country belongs, but we find no evidence that geographic factors sort countries into growth regimes once the quality of institutions is allowed to enter the estimation.

Paap, Franses, and van Dijk (2005) apply latent class models to a panel of countries allowing the growth rates data to determine the number of groupings. They find that a model assuming three groupings of countries is statistically superior to a model that assumes economies are homogeneous. In this aspect, our methodology is similar to the work by Paap, Franses, and van Dijk (2005).[1] However, this paper makes three additional original contributions. First, we examine growth rates in both developed and developing economies, unlike Paap, et. al. who only examine growth in developing countries. Second, by examining the conditional distribution of growth rates rather than the unconditional distribution, we are able to estimate the marginal effects of growth fundamentals within regimes. For example, we identify a group of countries for which initial income is negatively related to subsequent growth and one in which it is positively related. Finally, and most importantly, our method allows us to perform hypothesis testing on the sources of systematic heterogeneity that explain the assignment of countries to specific latent regimes in a way that ties our empirical results into the current growth literature.

[1] In addition to Paap, Franses, and van Dijk (2005), other applications of latent class models in the economics literature include Owen and Videras (2007) and Clark, Etile, Postel-Vinay, Senik, and Van der Straeten (2005). There are relatively few applications of finite mixture models in economics; see Boxall and Adamowicz (2002) and Greene and Hensher (2003).

Finally, the paper most closely related to our work is Alfo, Trovato and Waldmann (2008). As we do, they estimate a finite mixture model on a panel of 5-year growth rates for a large set of countries. They identify multiple growth regimes and speculate that the latent variable that defines the classes may be related to institutions.[2] Our analysis takes this as a starting point and extends the method employed by Alfo, et. al. by accounting for the sources of heterogeneity across countries. This methodology allows us to test which factors affect the latent variable sorting countries into growth regimes. We show that the quality of institutions does in fact help to predict the latent variable grouping countries. We are also able to simultaneously test alternative hypotheses as suggested by Bloom, et. al. (2003) that geographic characteristics determine growth regimes.

In comparing our work to the existing growth literature, we note that an important theme in both the empirical and theoretical growth literature is the existence of multiple equilibria.[3] Empirical estimation of models with multiple equilibria typically relies on using observable characteristics such as income or education levels to sort countries into regimes. Our work is related to this approach, with an important difference. Specifically, our methods allow us to sort countries into growth regimes based on an unobservable latent variable that is determined by the conditional distribution of growth rates and country characteristics that are often referred to as the "deeper determinants" of growth such as institutions and geography. Therefore, we believe our work extends this line of thinking because we are able to choose a number of country characteristics as indicators of the latent variable and statistically test the validity of these indicators. Furthermore, while the existence of "convergence clubs" may be a result of countries experiencing different growth processes, it does not necessarily have to be. Identifying these clubs is not the goal of our analysis; we examine a much broader phenomenon. In fact, our results suggest that conditional convergence occurs only within a subset of countries. For several countries in

[2] Alfo, Trovato and Waldmann (2008) find more classes than we do. However, because we are interested in testing hypotheses about institutional quality, we restrict our sample only to those countries for which we have data on institutional quality. Therefore, our data set is somewhat smaller which results in fewer classes.

[3] The literature on multiple equilibria in the growth process and convergence clubs is vast. Interested readers may want to see Azariadis and Stachurski (2005) for an introduction to this literature.

our sample, we do not find evidence that their incomes are converging to that of other countries in its grouping.

The remainder of the paper is organized as follows. The following section provides a theoretical framework for our results and discusses our choice of regressors and covariates. Section 3 presents our econometric approach. Section 4 presents and discusses our empirical findings, and the final section concludes.

2 Empirical Framework

The empirical model we estimate includes regressors that capture the proximate determinants of economic growth. Investment, education, and population growth are direct measures of the growth of productive factors. Initial income controls for transitional dynamics that occur when earlier gains are easier than later ones, either due to technical transfer or diminishing marginal returns to capital. Our estimations are based on a standard growth equation:

$$g_{i,t} = \beta_0 + \beta_y \ln(y_{0,i,t}) + \beta_K \ln(s_{i,t}) + \beta_H \ln(h_{i,t}) + \beta_L \ln(n_{i,t} + g + \delta) \qquad (1)$$

where $g_{i,t}$ is the 5-year average growth rate of real per capita income of country i in period t, $y_{0,i,t}$ is initial income in period t, $s_{i,t}$ is the average investment rate, $h_{i,t}$ is the average years of education of the labor force during the initial year of the period, $n_{i,t}$ is the average population growth rate over period t for country i, g is the growth rate of technology and δ is the depreciation rate. Following Mankiw, Romer and Weil (1992) we assume the annual rates of growth of technology and of depreciation are constant and sum to .05. The constant term captures increases in labor productivity that are orthogonal to factor accumulation and initial conditions.

As shown by Mankiw, Romer, and Weil (1992), this specification can be derived directly from a Cobb-Douglas production function with capital, labor and human capital as inputs. We will estimate Equation 1 with panel data. As will become clearer in Section 3, the technique that we describe below could be considered to be a non-parametric random effects model. The covariates we discuss below will help us to determine which countries can be grouped together. Admittedly, 5-year intervals may be the minimum length of time that will allow us to comment on factors affecting longer-run growth and we urge caution in interpreting the results. We discuss some attempts at applying this method to longer-term growth rates in Section 4.

The model in Equation 1 deliberately lacks novelty. The regressors are those suggested by the augmented neoclassical model employed by Mankiw, Romer and Weil (1992). They are also among the handful of variables identified by Levine and Renelt (1992) as being robust determinants of economic growth. While neither of these papers has gone unchallenged, they both exerted a large impact on later growth empirics, allowing comparison of our results with other empirical work on growth.

As we explain in more detail below, we also employ covariates that are not direct determinants of growth but help to sort countries into different growth regimes. This novel feature of our estimation allows us to present empirical results that are more consistent with the idea that some variables are proximate determinants of growth, while others may be considered "deeper" determinants in that they influence the overall environment in which growth occurs. (e.g., Rodrik, Subramanian, and Trebbi, 2004) In choosing our covariates, we focus on two categories of variables that the literature suggests play a central role in determining a country's growth process, and more particularly how it responds to capital accumulation, population growth and the dynamics of convergence. We proceed by choosing broad categories of country characteristics (institutions and geography) that have been suggested by a large body of work and then choosing indicators within each category that capture important features of this characteristic. An advantage of our approach is that it recognizes that these covariates are indicators of class membership with error. In other words, our procedure recognizes that there is some error associated with the process of assigning countries to classes and, as we discuss in the following section, we can attempt to gauge the error associated with our country groupings.

As there is an immense literature related to each of our covariates, we mention only briefly some of the previous work that motivated our choice to use measures of institutional quality and geography to sort countries into growth regimes. Institutions are widely held to play a significant role in economic growth. (See, for example, Mauro (1995), Acemoglu, Johnson and Robinson (2001), Dollar and Kraay (2003) and Rodrik, Subramanian and Trebbi (2004), among others.) Democratic political institutions in particular may also affect the economics of accumulation with a central thesis in the theoretical literature on democracy and growth being that populist policies may blunt incentives to invest in physical capital as in Alesina and Rodrik (1994) and Persson and Tabellini (1994), while also potentially subsidizing the accumulation of human capital as suggested by Bourguignon and Verdier (2000) and Benabou (2000).

Geography has also played a prominent role in the growth literature. As mentioned previously, in an article closely related to ours, Bloom, Canning, and Sevilla (2003) find that countries with cool, coastal locations have relatively high income, but that hot, landlocked countries with low rainfall are more likely to be in a poverty trap. Their work follows a number of studies that have linked climate and geographic features to economic performance. (See, Bloom and Sachs (1998), Sachs and Warner (1997) and Gallup, Sachs and Mellinger (1999) as just a few examples of this previous literature.)

Because we chose these covariates based on their prominence in the growth literature, our contribution to this literature is not to propose new growth determinants—it is to empirically model their effect in a fundamentally different way. In other words, we do not model these covariates as direct determinants of growth, but as indirect determinants that influence the environment in which growth occurs and the marginal productivity of the growth fundamentals.

3 Method: Finite mixture regression model

We use a finite mixture approach to estimate the growth regression model in Equation 1. This approach is an application of latent class regression models to estimate a latent discrete distribution of growth regimes. Our approach has four important features. First, the observed conditional distribution of growth rates is assumed to be a mixture of two or more distributions with different means and variances. Second, the parameters of the growth regression are allowed to differ across regimes. Third, the distribution of the latent regimes and the parameters of the growth regression for each regime are estimated jointly. Finally, in addition to accounting for heterogeneity in the growth process, finite mixture models can explain the sources of systematic heterogeneity. In our application, we explore whether indicators of institutional quality and geography can improve the model's fit and the assignment of countries to growth regimes.

Specifically, we assume that growth processes can be classified into M discrete classes. Letting T represent the number of repeated observations per country, $\boldsymbol{Z}$ be the vector of independent variables in Equation 1, and letting x indicate class membership, the probability structure for a given country is:

$$f(g_t \mid \mathbf{Z}_t) = \sum_{x=1}^{M} P(x) \prod_{t=1}^{T} f(g_t \mid x, \mathbf{Z}_t), \qquad (2)$$

where $P(x)$ is the probability of membership in latent class x and $f(g_t \mid x, \mathbf{Z}_t)$ is the distribution of growth rates conditional on membership in latent class x and independent variables. We assume the latent variable follows a multinomial probability that yields a standard multinomial logit model:

$$P(x) = \frac{\exp(\eta_x)}{\sum_{x'=1}^{M} \exp(\eta_{x'})}, \qquad (4)$$

where the linear predictor η_x is such that membership in class m is defined by:

$$\eta_m = \log\left(\frac{P(x=m)}{[\prod_{m'=1}^{M} P(x=m')]^{1/M}}\right) = \gamma_{m0}. \qquad (5)$$

Under this formulation, we compare the probability of being assigned to class m with the geometric average of the probabilities of all M classes.

We extend our analysis by examining the determinants of class membership. We use variables related to the quality of institutions and geographic features as covariates that help predict class membership. Denoting the vector of K covariates as $\mathbf{V}$, we can now write the probability structure for a model with covariates as:

$$f(g_t \mid \mathbf{Z}_t, \mathbf{V}) = \sum_{x=1}^{M} P(x \mid \mathbf{V}) \prod_{t=1}^{T} f(g_t \mid x, \mathbf{Z}_t). \qquad (6)$$

This approach differs from the standard treatment in the literature because we treat these covariates as indicators of growth regimes rather than direct determinants of growth. Importantly, we sort countries into growth regimes based on the combination of these indicators rather than on the value of specific indicators. Thus, our method is not simply a substitute for interacting the individual indicators with the regressors.

Now, the probability of latent-regime memberships is:

$$P(x \mid \mathbf{v}) = \frac{\exp(\eta_{x|\mathbf{v}})}{\sum_{x'=1}^{M} \exp(\eta_{x'|\mathbf{v}})}, \tag{7}$$

and:

$$\eta_{m|\mathbf{v}} = \log\left(\frac{P(x = m \mid \mathbf{v})}{[\prod_{m'=1}^{M} P(x = m' \mid \mathbf{v})]^{1/M}}\right) = \gamma_{m0} + \sum_{k=1}^{K} \gamma_{mk} v_k . \tag{8}$$

The model is estimated via maximum likelihood. In the case of the model with covariates, maximum-likelihood estimation involves finding the estimates of the beta parameters and the vector of gamma parameters $\boldsymbol{\gamma}_{mk}$ that maximize the log-likelihood function derived from the conditional probability density function in Equation 6. Assuming the error term in the growth rate equation comes from a normal distribution and adding subscript *i* to identify countries, the log-likelihood function is:

$$\log L = \sum_{i=1}^{I} \log f(g_{it} \mid \mathbf{z}_{it}, \mathbf{v}_i, \beta_0, \beta_y, \beta_K, \beta_H, \beta_L, \boldsymbol{\gamma}_{mk}) =$$

$$\sum_{i=1}^{I} \log[\sum_{x=1}^{M} P(x \mid \mathbf{v}_i) \prod_{t=1}^{T_i} f(g_{it} \mid x, \mathbf{z}_{it})] =$$

$$\sum_{i=1}^{I} \log[\sum_{x=1}^{M} \frac{\exp(\eta_{x|\mathbf{v}})}{\sum_{x'=1}^{M} \exp(\eta_{x|\mathbf{v}})} \prod_{t=1}^{T_i} f(g_{it} \mid x, \mathbf{z}_{it})], \tag{9}$$

where

$$f(g_{it} \mid x, \mathbf{z}_{it}) = \frac{1}{\sqrt{2\pi\sigma_m^2}} \exp\{-\frac{(g_{it} - \mu_m)^2}{\sigma_m^2}\}, \tag{10}$$

and μ_m and σ_m^2 are the mean and variance of the growth rate of the sub-population in class *m*. In the case of the model without covariates, the log-likelihood function of the model is the same as in Equation 9 but replacing $\sum_{x=1}^{M} P(x \mid \mathrm{v})$ with $\sum_{x=1}^{M} P(x)$.

We use Latent GOLD to perform the estimation. In practice, the likelihood functions for these types of models can feature local maxima. To ensure that we obtain the global maximum, we estimate each model using 10,000 sets of starting values. Each set might result in different log-posteriors. Latent GOLD uses the best solution until convergence (Vermunt and Magidson, 2005). We repeat the process twice to verify we obtain the same solution. In our application, we always obtain the same log likelihood for the same estimations, making us confident that we are obtaining global maxima for the models.

We use the empirical Bayes rule to calculate country-specific posterior membership probabilities for each country *i* = 1,…,N,

$$\hat{P}(x \mid v_i, g_i) = \frac{\hat{P}(x \mid v_i)\hat{P}(g_i \mid x, v_i)}{\hat{P}(g_i \mid v_i)}. \tag{11}$$

Because all of the parameters in the likelihood function (described in Equations 7, 8, 9 and 10) are estimated jointly, the posterior membership probabilities depend on both the value of the covariates and the distribution of growth rates.

Equation 11 emphasizes a key advantage of the finite mixture approach: the probability of class membership depends on the conditional distribution of growth rates and the covariates. Once we calculate the probability of class membership for each country using Equation 11, we use the empirical Bayes modal classification rule to assign countries into classes; that is, each country is assigned to the class for which it has the largest posterior probability. Although for most countries the classification occurs with posterior probabilities very close to 1, the classification is probabilistic. The quality of the classification for each country can be determined by the conditional probability of misclassification

$1-\max \hat{P}(x \mid v_i, g_i)$ and the overall misclassification rate errors by $E = \frac{\sum_{i=1}^{N}\left[1-\max \hat{P}(x \mid v_i, g_i)\right]}{N}$ (Skrondal and Rabe-Hesketh, 2004).

In practice, the number of classes is unknown to the researcher. We start with a one-class model and then estimate subsequent models that increase the number of classes by one each time. We use information criteria based on the model's log likelihood to select the model that best fits the data. We use three different information criteria to evaluate the models: the Bayesian Information Critera (BIC), the Corrected Akaike Information Criteria (CAIC) and the Akaike Information Critera 3 (AIC3). All three criteria are decreasing in the value of the log likelihood and increasing in the number of parameters estimated. Therefore, we choose the model with the lowest BIC, CAIC and AIC3. Specifically, the BIC= -2LL + log(N)J, the CAIC=-2LL+log(N+1)J, AIC3=-2*LL* + 3*J* where *LL* is the value of the log likelihood, N is the sample size, and *J* is the number of parameters estimated.[4] Once the model is selected, it is then possible to test for statistical significance of the regression coefficients, the differences between the regressions coefficients, and the usefulness of the covariates for sorting countries into classes.

4 Results and Discussion

4.1 Data and Results

Data

The dependent variable is the average annual growth of real GDP per capita over the 5-year periods 1970 to 1975, 1975 to 1980, 1980 to 1985, 1985 to 1990, and 1995 to 2000. The independent variables are the log of real GDP per capita in the initial year of each period, the log of average annual population growth rates + .05, the log of average investment rates, and the log of average years of

[4] The Akaike Information Criteria (AIC) can also be used to select models. It is calculated AIC=-2*LL*+2*J*, imposing a smaller penalty for additional parameters. When the model choice suggested by the AIC differs from that of the other criteria, typically the AIC indicates more classes because of the smaller penalty for additional parameters. In choosing the AIC3 over the AIC, we follow recent research that suggests the AIC3 is the best criterion to use in selecting the number of classes in a latent class or finite mixture model. See Andrews and Currim (2003) for further discussion of this issue.

schooling of the labor force in the initial year of the five-year interval. As has been discussed by many others, growth regressions of this type are plagued by endogeneity so we must be cautious in inferring causality. Nonetheless, we use this standard specification so that we can focus on the issue of the heterogeneity of growth processes while our results can be easily compared to others.

As mentioned above, we use institutional and geographic variables as covariates to help to predict class membership. The geographic variables we use are the absolute value of latitude and a dummy variable for whether a country is landlocked. These variables capture geographic features that are related to a country's agricultural and disease endowment and its natural degree of openness. To proxy for institutional quality, we first use European settler mortality rates. As argued by Acemoglu, Johnson, and Robinson (2001), settler mortality influenced colonization strategy and, thus, the development of growth-promoting institutions. In a second estimation we use indices of law and order and democracy to expand our sample beyond the European colonies. We use all the countries and all time periods for which all data are available. In the first model, without the covariates predicting class membership, we do restrict our sample only to those countries for which we have the settler mortality data so that our results are comparable. In this case, we have 265 observations from 47 countries. When we expand our sample by replacing settler mortality with indicators of current institutional quality, we have 426 observations from 74 countries. Table 1 provides descriptive statistics and the data sources.

Results

In this section we discuss the results of maximizing the log-likelihood function defined by Equation 9. As a preliminary step, we first estimate a model without covariates (but using the same sample as if we had included the covariates) to determine the number of classes that are defined by the conditional distribution of growth rates. As mentioned above, we consider several selection criteria for choosing the number of classes, each of which involve a trade-off between goodness of fit and the number of parameters. The fit statistics for models without covariates from one to five classes are presented in Table 2. As can be seen in this table, all three information criteria, the BIC, AIC3 and the corrected AIC suggest that the model that best fits the data is a two class model. In other words, from this exercise, we conclude that there are two different growth processes experienced by this sample of countries. Although not shown in Table 2, we also perform a likelihood ratio test (bootstrapping the p-values) to confirm that the two-class model is preferred over the one-class model.

To further explore what exogenous country characteristics help to predict to which growth regime a country belongs, we then add landlocked, latitude, and settler mortality as covariates. Table 3 presents the fit statistics for these models. As above, all three information criteria point to the two class model.[5] Even with the additional parameters estimated in these models, the two class model with these three covariates fits the data better than the two class model without the covariates by all measures. Specifically, this model has improved information criteria, an improved R-squared, and lower classification error.[6]

Table 4 displays the class membership for the individual countries in the sample along with the predicted probabilities of this membership. A couple of points are worth noting. First, certainty of classification is high for most countries: as can be seen from this table, the majority of countries are in Class 1 and many countries in Class 2 are placed in their classes with high probability. Second, the countries in Class 2 do not all share the same observable characteristics such as region or income that are typically used to group countries. As shown in Table 5, they tend to be faster growing countries, with lower rates of settler mortality, less likely to be landlocked, and are farther away from the equator. That said, Class 2 is admittedly small, possibly because use of the settler mortality data restricts our sample, specifically excluding the European colonizers. We take up this issue with an expanded sample in subsequent estimations.

The estimated coefficients for the growth regressions and the covariates from this estimation are displayed in Table 5. In the first column of Table 5, the one-class model is presented and in the second and third columns, results of the two class model appear. Because class 1 is such a large part of the

[5] It is true that the AIC3 for the four class model is very slightly lower than it is for the two class model. However, given that the BIC and the corrected AIC point to the two class model, we justify ignoring this small difference on the basis of parsimony.
[6] Likelihood ratio tests with bootstrapped –values also prefer the two class model with covariates over the one-class model with covariates.

sample, the one-class model mirrors the results for Class 1 of the two-class model. However, the majority of the coefficients for Class 2 are statistically different from those of Class 1, suggesting that these countries follow a different growth process. Specifically, Column 4 of Table 5 reports the p-value of the Wald tests for the equality of coefficients across classes. These results indicate that except for the coefficient on investment, all the remaining coefficients for Class 1 and Class 2 are statistically different from each other. Thus, using the results for the one-class model for these countries could lead to incorrect conclusions.

In the two-class model, countries are sorted into classes based on a latent variable. What helps to predict this latent variable? The coefficients that are reported in the bottom half of Table 5 for each covariate correspond to the gamma parameters γ_{mk} in equation 8. These coefficients are reported relative to Class 1. In other words, a positive coefficient indicates that higher values of the covariate are associated with greater probability of membership relative to membership to Class 1. The results for the covariate coefficients suggest that the latent variable sorting countries into different growth regimes is related to the quality of institutions. Of the three covariates, only settler mortality is significant, suggesting that institutional quality is responsible for sorting the countries into the classes. Of course, settler mortality may be affected by geographic features of countries and when we run the model without settler mortality, the two geography variables have increased statistical significance. Landlocked predicts membership in Class 2 negatively (at the 1% level) and latitude positively predicts Class 2 membership, though with lower significance (p-value of .14). The fact that these geography variables no longer are significant once settler mortality is incorporated into the estimation suggests that geography may play a role in sorting countries into growth regimes through its effect on institutional development.

Unfortunately, as we mentioned above, although settler mortality has the advantage of being clearly exogenous, its use excludes countries that were not colonized by Europeans. In order to draw accurate conclusions about country characteristics that sort countries into classes, the covariates we use should be exogenous to the growth process. Although there is a correlation between current quality of institutions and level of income, it may be justifiable in our context to argue that current institutional features of the economy are exogenous to the five year growth rates. The arguments in Acemoglu, Johnson, Robinson and Yared (2008) support our reasoning. They provide evidence that democracy and income are contemporaneously correlated because they started to develop simultaneously centuries ago. Therefore, we replace settler mortality with two measures of current institutional quality, democracy and law and order, allowing us to almost double our sample size.

Using the expanded data set, we again estimate models with one to five classes and display the fit statistics in Table 6. Although in this case the AIC3 indicates a 3-class model, both the BIC and the corrected AIC suggest a 2-class model. Therefore, we choose the more parsimonious model again and display the country groupings in Table 7. As before, Class 2 contains faster growing countries, but, also as before, countries in this group are not all easily classified by the typical region or income groupings. Importantly, by expanding the sample to include countries that were not colonized by Europeans, we have added several countries in Class 2. A larger Class 2 emphasizes the importance of allowing heterogeneity in the growth process because it becomes clearer that there are more than just a few countries who do not conform to the Class 1 results.

Regression results appear in Table 8. The regression results of Class 1 and Class 2 regression results are different to the one-class model results. In addition, the Wald tests presented in Column 4 of Table 8 show that both the coefficient on initial income and the coefficient on human capital are different for both Class 1 and Class 2, suggesting that the effect of increased education and increased income would be different, depending on which class the country experiencing the change is in. An examination of the regression results for each class also leads to some interesting conclusions. The estimated growth regression for Class 1 countries is consistent with a neoclassical, accumulation-driven growth process. The same conclusion cannot be drawn for Class 2 countries. This regression shows a positive and significant coefficient on initial income, suggesting a lack of income convergence and the potential for multiple equilibria within this group. The negative coefficient on average years of education, however, suggests that there may be some convergence forces at work as countries with a more educated labor force grow more slowly.

As before, institutional quality seems to be the most important predictor of class membership, with law and order being a significant and positive predictor of membership in Class 2. In contrast, the democracy index is not a significant predictor of class membership. A perusal of the list of Class 2 countries in Table 7 provides insight into this result. Class 2 contains several strong democracies but also some less-democratic, fast-growing countries too. This result parallels earlier work that found that political institutions were less important for growth than economic institutions, (e.g. Knack and Keefer, 1995).

In general, our results lend some support to the common practice of treating rich and poor countries separately, but they also suggest that this practice is far from perfect. Controlling for the influence of relative backwardness on growth simply by using separate samples of rich and poor countries fails to take into account significant heterogeneity among countries at similar levels of development. Although Class 1 contains only developing countries, Class 2 contains both developed and developing countries. Interestingly, it is the developing countries in Class 1 that feature accumulation-driven growth. The growth process experienced by the faster-growing Class 2 countries is more difficult to explain with existing growth theories, except to note that the positive coefficient on initial income is consistent with these countries being responsible for pushing out the technological frontier.

Calculations in Table 9 compare the effects of the coefficients from the two-class model with those from a standard one-class model. The last two columns of Table 9 show the difference in the predicted growth effects of a one-standard deviation increase in each regressor for the two-class and one-class model. While the differences are smaller and statistically insignificant between the Class 1 results and the one-class model, these results show that using the standard, one-class approach to make inferences about Class 2 countries could lead to meaningfully different conclusions.

Policy Implications

Although so far our analysis has mainly been descriptive, if we were to infer a causal role for either the covariates or the regressors in the growth process, the policy conclusions would come at two levels. First, one type of policy conclusion would address the question: Given the growth process in a particular country (i.e., the class the country is in), what should be the focus of growth enhancing policy? For example, investment in education might be recommended for countries in Class 1 but might not necessarily be a growth priority for countries in Class 2.

Perhaps the more interesting conclusion is the answer to the question, what should a country do to move to a different group? Countries in Class 1 experience an average growth rate of 1.17. However, the "typical" country in Class 1 (one that has average values of initial income, investment, human capital and population growth for Class 1) would grow at 3.81 percent per year if its growth process were described by the coefficients estimated for Class 2. The disparity in growth rates associated with applying different estimates of the effects of these growth fundamentals more than explains the difference in growth rates. Our results then have a clear policy implication for institutional reform that generates greater law and order in developing countries.

Extensions

Although we use panel data looking at growth over 5-year intervals, our methods can also theoretically be applied to data that measures growth over longer periods (i.e., cross-section regressions examining 30 or 40 year growth rates or a shorter panel examining 10-year growth rates). Unfortunately, the methods are inherently data intensive and finding a parsimonious model that is consistently selected by all three information criteria with the smaller data sets necessarily generated by these longer term growth rates is not possible at this time.

We should also point out that, in the results we report, we examine five-year growth rates, but we constrain countries to be in the same class over the entire period. It is also possible to extend our methods to allow regime switching (i.e., countries switch classes over the period) via a Markov process. However, when we estimate models with this switching feature, we are unable to identify a model that fits the data better than the ones in which countries are constrained to stay in the same class. This finding is in contrast to that of Paap, Franses and van Dijk (2005) who find instability in the groupings of countries based on unconditional growth rates. This different result may be due to the fact that we examine the conditional distribution of growth rates or because of our use of 5 year average growth rates rather than one-year growth rates. Our covariates, which do not change or change very little over our sample period, are likely influencing our finding of stability. Nonetheless, such a model also fits well with the theoretical literature that addresses regime-switching and it is a fruitful area for further research.

4.3 Comparison to standard methods

In the model we presented above, variables proxying for institutional quality and geographic characteristics were used as covariates to help predict the growth regime to which a country belongs. This is in contrast to a standard treatment of variables like this in which they are entered separately as regressors in a one-class model. Before concluding, we also present these standard results and demonstrate that our methods not only fit the data better, but provide results that have a richer interpretation.

The results in Table 9 corroborate those found by many others - a negative and significant coefficient on initial income and a positive and significant coefficient on investment and schooling. The coefficient on law and order is positive and significant in this regression, but its interpretation is different. In our method, law and order is not a direct determinant of growth as it is in Table 9, it is a variable that influences the growth process by helping to sort countries into different growth regimes. Further comparison of these standard results to the two class model also shows that the two class model fits the data better in terms of having a lower AIC3, BIC, corrected AIC, and a higher R^2, allowing us to confidently reject this standard approach in favor of the two class model.

5 Conclusion

This paper presents a novel application of finite mixture models for estimating growth equations. Our results suggest that countries follow more than one growth process and that the quality of institutions is an important factor that helps to sort countries into different regimes. An important implication of these findings is that pooled, one-class analysis that overlooks the heterogeneity in the growth process can lead to incorrect conclusions about growth in many countries.

The main contribution of our work is to present an empirical technique that matches up with the theoretical ideas that consider growth to be influenced by both proximate determinants and "deeper determinants." In our framework, country characteristics such as quality of institutions influence the environment in which growth occurs and therefore affect the entire process of growth, determining the effects of the accumulation of factors of production.

Table 1: Descriptive Statistics

Variable	Obs.	Mean	SD	Description	Data Source
GROWTH	426	1.75	2.84	Average annual growth rate over 5 year period	PWT 6.2
$Ln(y_0)$	426	7.85	1.49	Log of initial income	PWT 6.2
Ln(s)	426	2.76	.530	Log of investment rate	PWT 6.2
Ln(h)	426	1.54	.663	Log of initial average years of education of labor force	Barro and Lee data set
$Ln(n+g+\delta)$	426	1.89	.160	Log of population growth + technology growth + depreciation rate	PWT 6.2, $g+\delta$ assumed to be .05
Law and Order	426	.621	.240	Index of law and order	ICRG
Democracy	426	.676	.212	Index of democracy	ICRG
Latitude	426	.296	.192	Absolute value of latitude	La Porta, Lopez, Shleifer, Vishny (1998)
Landlocked	426	.147	.355	=1 if landlocked	Author's calculations
Settler Mortality	265	4.42	1.10	Log of European settler mortality	Acemoglu, Johnson and Robinson (2001)

Table 2: Fit Statistics for Model without Covariates

	Log Likelihood	BIC	AIC3	CAIC	k	Clasification Error	R^2
1-Class Regression	-627.289	1277.678	1272.578	1283.6784	6	0	0.139
2-Class Regression	**-609.505**	**1269.062**	**1258.01**	**1282.0615**	**13**	**0.0512**	**0.2127**
3-Class Regression	-600.417	1277.836	1260.833	1297.8362	20	0.0591	0.2363
4-Class Regression	-592.935	1289.825	1266.871	1316.8248	27	0.0976	0.3045
5-Class Regression	-583.625	1298.156	1269.251	1332.1558	34	0.0983	0.3484

Table 3: Fit Statistics for Model using Landlocked, Latitude and Settler Mortality as Covariates

	Log Likelihood	BIC	AIC3	CAIC	k	Classification Error	R^2
1-Class Regression	-627.289	1277.678	1272.578	1283.6784	6	0	0.139
2-Class Regression	**-601.828**	**1265.259**	**1251.657**	**1281.2592**	**16**	**0.0039**	**0.232**
3-Class Regression	-587.943	1275.99	1253.886	1301.9901	26	0.0361	0.2603
4-Class Regression	-571.618	1281.842	1251.237	1317.8418	36	0.0011	0.2763
5-Class Regression	-559.453	1296.012	1256.905	1342.0121	46	0.0249	0.3382

Table 4: Class Membership, Model using Landlocked, Latitude and Settler Mortality Covariates

Class 1	Probability of Class 1 Membership	Class 2	Probability of Class 2 Membership
Algeria	≈1	Australia	0.999414
Argentina	≈1	Canada	0.995473
Bangladesh	≈1	Egypt	0.973955
Bolivia	≈1	Malaysia	0.986418
Brazil	≈1	Mauritius	0.990175
Chile	≈1	New Zealand	0.962111
Colombia	0.999936	Singapore	0.999947
Costa Rica	0.997816	Sri Lanka	0.917423
Dominican Republic	0.999997	United States	0.998699
Ecuador	0.999929		
El Salvador	≈1		
Ghana	≈1		
Guatemala	≈1		
Guinea-Bissau	≈1		
Honduras	≈1		
India	≈1		
Indonesia	0.998487		
Jamaica	≈1		
Kenya	≈1		
Mali	≈1		
Mauritania	0.999099		
Mexico	0.999998		
Nicaragua	≈1		
Niger	≈1		
Panama	0.999998		
Papua New Guinea	≈1		
Paraguay	0.999997		
Peru	≈1		
Rwanda	≈1		
Senegal	≈1		
Sierra Leone	≈1		
South Africa	≈1		
Tanzania	≈1		
Trinidad and Tobago	≈1		
Tunisia	≈1		
Uganda	0.999051		
Uruguay	≈1		
Venezuela	≈1		

Countries are placed in classes using empirical Bayes modal estimation.

Table 5: Growth regression results for model with covariates

	(1)	(2)	(3)	(4)
Variable	One Class Model (OLS)	Class 1	Class 2	p-value for Wald statistic for equality of coefficients across classes
Ln(y_0)	-.7586*** (.2642)	-0.8449** (.3202)	.079 (0.1548)	.01
Ln(s)	2.098*** (.4508)	1.7321*** (.4105)	1.9587*** (0.2209)	.63
Ln(h)	1.1240** (.4500)	1.1354** (0.4853)	-4.4452*** (0.8854)	.00
Ln(n+g+δ)	.1383 (1.3673)	.2712 (1.3563)	-5.5546* (3.2327)	.10
Constant	-.1106 (2.9179)	0.6645 (3.0398)	15.7242*** (6.5369)	.04
Covariates				
Settler Mortality			-2.5781*** (0.8008)	
Latitude			-1.2844 (2.6111)	
Landlocked			-1.2427 (1.095)	
R^2	.14	.10	.61	
Class Size (% of observations)	1.00	.81	.19	
Mean Growth Rate	1.23	.84	3.26	
Mean Settler Mortality	4.42	4.81	3.04	
Mean Latitude	.19	.17	.28	
Mean Landlocked	.12	.15	.00	

All estimations include a constant. Robust standard errors are in parentheses. *significant at 10%, **significant at 5%, ***significant at 1%

Coefficients for covariates are reported relative to class 1.

Table 6: Fit Statistics for model using Latitude, Landlocked, Democracy and Law and Order as Covariates

	Log Likelihood	BIC(LL)	AIC3(LL)	CAIC(LL)	K	Classification Error	R^2
1-Class Regression	-1003.95	2033.728	2025.903	2039.728	6	0	0.1882
2-Class Regression	**-942.929**	**1959.026**	**1936.857**	**1976.026**	**17**	**0.0262**	**0.3357**
3-Class Regression	-919.81	1960.133	1923.619	1988.133	28	0.0457	0.3526
4-Class Regression	-904.879	1977.617	1926.758	2016.617	39	0.0868	0.4276
5-Class Regression	-890.339	1995.882	1930.679	2045.882	50	0.0828	0.4516

Table 7: Class Membership, Model using Landlocked, Latitude, Law and Order, Democracy

Country	Probability of Class 1		Probability of Class 2
Argentina	0.999998	Australia	0.995101
Bangladesh	1	Austria	0.999852
Bolivia	1	Belgium	0.998886
Brazil	0.999999	Botswana	1
Chile	0.999862	Canada	0.99893
Colombia	0.999982	Switzerland	0.999687
Costa Rica	0.997679	China	0.870067
Cyprus	0.998676	Denmark	0.999096
Dominican Republic	0.999201	Egypt	0.992165
Algeria	1	Spain	0.816007
Ecuador	1	Finland	0.987361
Ghana	1	France	0.995731
Guinea-Bissau	1	UK	0.989437
Greece	0.694932	Hungary	0.986399
Guatemala	0.999969	Israel	0.761066
Honduras	1	Italy	0.995547
Indonesia	0.999952	Japan	0.993562
India	1	Korea, Rep.	0.857863
Ireland	0.99807	Netherlands	0.998604
Iran, Islamic Rep.	1	Norway	0.997969
Jamaica	1	New Zealand	0.996217
Jordan	1	Poland	0.866006
Kenya	1	Portugal	0.903936
Sri Lanka	0.999801	Singapore	0.998277
Mexico	0.999348	Sweden	0.998383
Mali	1	Uganda	0.870867
Malaysia	0.517952	USA	0.987587
Niger	1		
Nicaragua	1		
Panama	1		
Peru	1		
Philippines	1		
Papua New Guinea	1		
Paraguay	1		
Senegal	1		
Sierra Leone	1		
El Salvador	0.999982		
Thailand	1		
Trinidad and Tobago	0.999959		
Tunisia	0.999182		
Turkey	0.999649		
Tanzania	1		
Uruguay	0.999913		
Venezuela	1		
South Africa	0.999998		
Zambia	1		
Zimbabwe	1		

Table 8: Growth regression Results for expanded sample

	(1)	(2)	(3)	(4)
Variable	One Class Model (OLS)	Class 1	Class 2	p-value for Wald statistic for equality of coefficients across classes
Ln(y_0)	-0.5251** (.2128)	-1.0855*** (.2914)	1.5568*** (.2021)	.00
Ln(s)	2.4289*** (0.4039)	2.1251*** (0.5845)	1.4337 (1.7876)	.75
Ln(h)	0.5015 (.3489)	1.2806*** (0.4439)	-7.0309*** (1.7985)	.00
Ln(n+g+δ)	-1.3215 (1.3002)	-2.9622* (1.7682)	-6.8274 (8.6135)	.66
Constant		7.6721** (3.7793)	11.3477 (14.9745)	.80
Covariates				
Law and Order			10.2372*** (3.3623)	
Democracy			0.432 (3.0135)	
Latitude			-.0365 (11.0145)	
Landlocked			-0.9167 (1.7812)	
R^2	.19	.15	.70	
Class Size (% of observations)	1.00	.64	.36	
Mean Growth Rate	1.75	1.17	2.89	
Mean Law and Order	.62	.48	.86	
Mean Democracy	.68	.57	.84	
Mean Latitude	.30	.20	.46	
Mean Landlocked	.15	.13	.18	

All estimations include a constant. Robust standard errors are in parentheses. *significant at 10%, **significant at 5%, ***significant at 1%

Coefficients for covariates are reported relative to class 1.

Table 9: Comparing the One-Class and Two-Class Models

		Difference in Predicted Growth Rate, Percent Per Year	
Variable	Standard Deviation	Class1	Class2
$\ln(y_0)$	1.49	-.83	3.10***
$\ln(s)$	.530	-.16	-.531***
$\ln(h)$	.663	.52	-4.99***
$\ln(n+g+\delta)$	.160	-.27	-.88***

Asterisks indicate that the coefficients used to calculate the difference in predicted growth rates are significantly different than the point estimate from the one-class model. ***significant at 1%, **significant at 5%

Table 9: Standard Growth Regression

Variable	
Ln(y_0)	-1.1864*** (.2611)
Ln(s)	2.3287*** (.4379)
Ln(h)	.9647** (.3822)
Ln($n+g+\delta$)	-1.8598 (1.8074)
Law and Order	3.5284** (1.4881)
Democracy	-1.3443 (1.3292)
Latitude	1.0738 (1.3248)
Landlocked	-.8057 (.6735)
BIC	2033.40
CAIC	2043.40
AIC3	2020.36
R^2	.22
Class Size (% of observations)	1.00

All estimations include a constant. Robust standard errors are in parentheses. *significant at 10%, **significant at 5%, ***significant at 1%

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