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Do all Countries Grow Alike?

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Abstract

This paper investigates the driving forces of output change in 77 countries during the period 1970-2000. A flexible modeling strategy is adopted that accounts for (i) the inefficient use of resources, and (ii) different production technologies across countries. The proposed model can identify technical, efficiency, and input change for each of three endogenously determined regimes. Membership in these regimes is estimated, rather than determined ex ante. This framework enables explorations into the determinants of output growth and convergence issues in each regime.

Keywords: growth, efficiency, stochastic frontier analysis, latent class, regimes

JEL classification: C33, O33, O47

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1. Introduction

Over the past thirty years, significant effort has focused on providing answers as to why some countries produce more than others. Yet, growth differentials across countries still pose a puzzle to economists. Standard economic models imply that the output level in an economy depends entirely on the inputs used. For example, growth empirics typically base cross-country regressions on a neoclassical production function specification (Mankiw et al. 1992; Islam 1995), often expanded to include various sets of additional variables in an attempt to explain economic growth.[1] However, considerable disagreement remains regarding the explanatory variables to be included in the analyses (see Temple, 1999, for a comprehensive survey). The perceived failure of simple textbook models has stimulated a great deal of interest in providing alternative theories of growth. Endogenous growth theory emphasizes factors such as increasing returns to scale, technology spillovers, learning-by-doing, and unobserved factors (e.g., human capital), whereas the international economics literature (Krueger, 1998; Dollar and Kraay, 2004) stresses the openness of countries as an important conduit for growth.

This article develops a modeling strategy and presents empirical evidence that provides further insights into the determinants of nations' growth. A structural methodology is adopted that allows for the decomposition of output change into efficiency, technical, and input change across a large panel of developed and developing countries. The aim of the paper is to investigate whether all countries use the same production function, the sources of output growth, and if there is evidence of convergence. Policy implications of these results are discussed also.

Traditionally, cross-country growth empirics have assumed the efficient use of inputs. The strong assumption that economic units (countries) are always efficient (i.e., they always produce at the production possibility frontier) implies that actual output is the maximum attainable output and that all countries are equally productive for a given level of inputs. In reality, however, economic units may use the best-practice (frontier) technology with varying degrees of efficiency. As a result, parameter estimates for the marginal effects of inputs are biased in the presence of inefficiency. Efficient countries may increase their output through technical change (i.e., shift of the frontier), whereas inefficient countries may increase output by becoming more efficient through the use of the best-practice technology.

Here, we account for inefficiency and estimate a stochastic production frontier, which is the empirical analog of the theoretical production possibility frontier. This modeling strategy therefore adds structure to the unexplained residual. Under reasonable assumptions, it disentangles the residual into inefficiency and measurement error. Given this framework, we can decompose output changes into three types of change: technical change (i.e., shifts of the frontier over time), efficiency change (i.e., movements of a country toward or away from the frontier), and input change (i.e., scale elasticity-adjusted changes in factor use).

A growing body of recent empirical literature has conducted efficiency analyses along lines similar to that we propose in this paper, but has used different modeling approaches. Previous studies have decomposed output change into technical, efficiency,

[1] See Barro (1991), Levine and Renelt (1992), Persson and Tabellini (1994) and others.

and input change. For instance, Färe et al. (1994) use data envelopment analysis (DEA), while Koop et al. (1999, 2000) and Limam and Miller (2004) apply stochastic frontier analysis (SFA) to examine country-specific inefficiency in a number of developed and developing countries. [2] However, not all countries necessarily share a single common frontier. [3] With the exception of a handful of studies that allow for parameter heterogeneity when estimating frontier production functions, the frontier literature has largely ignored this issue.

Similarly, conventional cross-country growth empirics mainly examine the `average' country (Temple, 1999) via an universal growth model that governs the (per capita) output evolution in all countries. However, if growth patterns diverge across countries, the `average' country is not representative, parameter averages are less informative about the factors that matter for a particular country (Solow, 1994), and no country benefits from one-size-fits-all policy recommendations. More generally, the validity of treating all countries as a single homogeneous group, for which the same variables have the same effect on economic growth, seems increasingly questionable (see Brock and Durlauf, 2001 for an extensive discussion of this issue).

In response to these concerns, a range of methodologies have been proposed. For example, Durlauf and Johnson (1995) employ classification and regression tree analysis, which identifies threshold values in particular economic variables (e.g., output per capita, adult literacy rates, etc.), to determine the appropriate grouping of countries. [4] Rather than classifying countries *ex ante* into various groups on the basis of geographic location or threshold values of particular economic variables, Paap et al. (2005) and Davis et al. (2007) apply latent class models that sort countries into different growth regimes according to the similarities of their economic growth rates. They find that a model with three and four groups of countries, respectively, is statistically superior to a model that assumes economies are homogeneous. To improve the country classification, Davis et al. (2007) explore the conditional (i.e., on institutions, openness, and macroeconomic policy) distribution of countries' growth rates.

Some authors in the frontier literature have attempted to account for heterogeneity in growth patterns. In exploring the sources of output differentials in a panel of developed

[2] Various studies also investigate the role of efficiency in explaining growth differentials for a panel of manufacturing industries in OECD countries. See, for instance, Koop (2001) and Kneller and Stevens (2006).

[3] Theoretical contributions (Basu and Weil, 1998; Acemoglu and Zilibotti, 2001) stress the `appropriateness' of technology, suggesting that countries choose the best technology available to them, given their input mix. On empirical grounds, a number of works have emphasized that labor and capital cannot be equally productive in all countries (Trefler, 1993; Tallman and Wang, 1994; Auerbach et al., 1994). Countries are members of the same technology class if their marginal productivity of labor and capital (the technology parameters that characterize the efficient production frontier) are the same for a given level of inputs such that their input/output combinations can be described by the same production frontier (Jones, 2005).

[4] A number of studies continue in this tradition. Papageorgiou (2002) extends the work of Durlauf and Johnson (1995) by exploring whether trade can be used as a threshold variable. Desdoigts (1999) proposes clusters based on culture, geographic location, and OECD membership. Hobijn and Franses (2000) use a clustering method as well, and find an abundance of convergence clusters. More recently, Bloom et al. (2003), Canova (2004), and Sirimaneetham and Temple (2006) explore the existence of multiple growth regimes. For instance, Sirimaneetham and Temple (2006) sort economies into groups according to the value of an index of policy quality. Bloom et al. (2003) argue that geographical variables determine the likelihood that a country will be assigned to the two regimes they find. Canova (2004) takes a Bayesian approach to examine income levels in Europe and, using initial income as a splitting variable, finds four groups of countries.

and developing countries, Koop et al. (2000) and Limam and Miller (2004) controlled for the quality of production factors using effective labor and capital, instead of actual labor and capital, and estimate regional frontiers. [5] The geographic division of the sample is to a certain degree subjective, as some authors readily admit, and models may be poorly identified because of the lack of data for some regions such as Africa and Asia (see Koop et al., 2000, pages 286-287). Tsionas and Kumbhakar (2004) instead proposed a stochastic frontier production function augmented with a Markov switching structure to account for different technology parameters across heterogeneous countries. Technology group membership depends on priors in their Bayesian framework. Others, for example Koop et al. (2000), critically view forming technology club memberships based on priors.

In this paper we allow for heterogeneous growth experiences. Whereas most studies that classify countries apply an *ex ante* sorting based on characteristics such as income and geography, we endogenize the sorting of countries using a latent class model. The latent class approach supposes a simple parametric model and uses observed data to estimate parameter values for each regime in the model. Among the parameters estimated is the probability that a certain country in a particular time period is a member of one of the regimes. These probabilities result from a (multinomial logit) sorting equation and depend on observable characteristics. In our case these characteristics are conditioning variables common to the growth literature (Durlauf and Johnson, 1995; Koop et al., 2000; Papageorgiou, 2002; Davis et al., 2007) - - namely, the level of human capital, openness to trade, financial development and the primary sector share. We thus estimate a regime-specific coefficient for each production factor. Each regime exhibits `conditional independence' because each variable is statistically independent of every other variable.

Hence, we advance methodology by introducing a structural and flexible model that allows simultaneously for (i) the inefficient use of resources, and (ii) different technologies across countries. We augment the stochastic frontier production model with a latent class structure, as proposed by Greene (2002a) and Orea and Kumbhakar (2004). Using regime-specific production parameters, we identify technical, efficiency, and input growth for endogenously determined regimes. We introduce additional flexibility into the model by permitting countries to switch between regimes over time. The efficiency of countries in different regimes is estimated simultaneously but relative to each regime's specific frontier. The latent class stochastic frontier model enables us to avoid the routinely imposed assumption of a common production function for all countries but yields results that are comparable across countries at a given point in time.

Our work relates to and extends several important studies. Paap et al. (2005) and Davis et al. (2007) also apply latent class models to investigate growth experiences across a panel of countries. We extend their work by accounting for the inefficient use of resources and allowing countries to change regimes. In relation to the frontier literature, particularly studies by Koop et al. (1999), Koop et al. (2000), Koop (2001), Limam and

[5] Koop et al. (2000) use the years of schooling embodied in the workforce to correct for labor and agriculture and industry labor force participation to correct for physical capital. They also allow for four different production frontiers: one for western industrialized economies, one for East Asia, one for Latin America, and one for Africa. Limam and Miller (2004) use the mean years of education and average age of physical capital to account for quality of labor and physical capital, respectively. Like Koop et al. (2000), they allow for heterogeneity by estimating regional frontiers based on five geographic devisions: Africa, East Asia, South Asia, Latin America, and the West.

Miller (2004), Tsionas and Kumbhakar (2004), and Kneller and Stevens (2006) which control for heterogeneity in growth patterns across countries, we further account for heterogeneity in the growth patterns of countries without following *ad hoc* or *a priori* clustering. Instead, we endogenize the regime allocation by applying a latent sorting, conditioned on growth determinants commonly used in prior literature.

Our empirical analysis is based on a sample of 77 countries during the period 1970-2000, whereas similar studies generally examine fewer countries over a shorter time span (Koop et al., 1999, 2000; Koop, 2001; Limam and Miller, 2004; Tsionas and Kumbhakar, 2004; Paap et al., 2005; Kneller and Stevens, 2006; Davis et al., 2007). We proceed with our empirical analysis with three primary questions in mind: (i) Do all countries follow the same growth experience?; (ii) What are the sources of growth?; and (iii) What economic theory provides a reasonable description of the growth processes?

Our results are easy to summarize. We find no evidence that countries follow a common growth process, nor do we find that the growth process of each country is entirely unique. Rather, we identify three distinct growth processes or growth regimes. First, the mature regime with most observations, which hosts many European countries and the United States is characterized by high human capital accumulation. Second, the emerging regime, which contains many Asian countries, is characterized by a relatively high level of financial development. And third, the developing regime with many African countries is characterized by a large primary sector share and high degree of openness. Almost all regimes include countries from various geographical regions and/or income groups. Therefore, assigning countries *ex ante* to certain groups based on their income or regional criteria is not appropriate. We do find, however, that many countries from the same region or with the same development level cluster in the same regime.

Efficiency is economically and statistically important. Whereas the neoclassical paradigm assumes that countries are fully efficient, we demonstrate the fallacy of this assumption, since efficiency levels vary across regimes. We find countries that belong in the emerging regime exhibit the highest level of efficiency, whereas the least efficient countries tend to be members of the developing regime.

The driving forces of growth also vary across and within regimes. A consistent finding across all regimes shows that input accumulation is an important source of growth, a finding we share with Koop et al. (1999, 2000) and Limam and Miller (2004), among others. Our findings suggest that countries' growth patterns do not necessarily support just one growth explanation, such as the input accumulation view or the productivity view. Instead, explaining countries' growth performance requires a more pluralistic interpretation.

Countries can grow within a regime by catching up with the frontier (convergence) or migrating to a better regime (switching). Our results show that with the exception of few countries, regime allocation is fairly stable, and countries change only rarely across regimes. Most migrations pertain to countries switching between the mature and the emerging regime. With regard to convergence, we find strong evidence of `convergence clubs' as different regimes converge at different rates to their regime's steady-state.

Overall, many of our findings could not have been obtained using traditional approaches, such as imposing constant returns to scale, ignoring inefficiency, assuming a single, common production function. By adopting a flexible modeling approach, we gain additional insights into policies that should foster growth. We find no support for the one-size-fits-all policy. More education alone, for instance, may put countries in more advanced regimes, but for education to be effective it needs the support of other development measures, such as enhanced factor allocation, financial development, and trade policies. The presence of significant inefficiency in one of the regimes further suggests that development policies geared toward a better exploitation of existing technologies, rather than promoting technical advances to push the production possibility frontier, might be beneficial for some countries.

The remainder of this paper proceeds as follows. Section 2 presents the methodology and the econometric specification for estimation. Section 3 discusses the data. Empirical results are presented in Section 4. Section 5 concludes.

2. Methodology

We first introduce a model of production that accounts for inefficiency. We then augment the model with a latent class structure to allow for more than one type of production. Finally, we decompose the output change for each regime into technical, efficiency, and input change.

2.1. *A Stochastic Frontier Model of Production*

We model the performance of countries using a stochastic frontier production model. [6] A frontier production function defines the maximum output attainable, given the current production technology and available inputs.

If all industries produce at the boundary of a common production set that consists of an input vector with two arguments, physical capital (K) and labor (L), output can be described as:

$$Y_{it}^{*} = f(X_{it}, t; \beta) \exp\{v_{it}\}, \quad (1)$$

where Y_{it}^{*} is the frontier (optimum) level of output in country i at time t; X_{it} is the vector of inputs, namely, physical capital, K_{it}, and labor, L_{it}; f and the parameter vector β characterize the production technology; t is a time trend variable that captures neutral technical change (Solow, 1957); and v_{it} is an i.i.d. error term distributed as $N(0, \sigma_v^2)$, which reflects the stochastic character of the frontier.

Two aspects of equation (1) are worth noting. First, the frontier represents a set of maximum outputs for a range of input vectors. Therefore, at any moment in time, it is defined by observations from multiple countries, not just one. This definition differentiates our modeling approach from conventional empirical growth approaches in which the leader country achieving the highest level of total factor productivity (TFP), constitutes the frontier (Bloom et al., 2002; Cameron et al., 2005). An implicit but nontrivial assumption in this literature suggests that technical progress is described by the observations of a single country over time. Second, our modeling approach treats the frontier as stochastic by including the error term v_{it}, which accommodates noise in the data and therefore allows for statistical inference. In this respect, it fundamentally differs from other (non-parametric) frontier industry-level analyses (Färe et al., 1994; Kumar and

[6] Stochastic frontier analysis (SFA) was introduced by Aigner et al. (1977), Battese and Corra (1977), and Meeusen and van den Broeck (1977).

Russell, 2002; Los and Timmer, 2005) that do not allow for random shocks around the frontier.[7]

Some countries, however, may lack the ability to employ existing technologies efficiently and subsequently produce less than the frontier output. If the difference between optimum and actual (observable) output is represented by an exponential factor, $\exp\{-u_{it}\}$, then the actual output, Y_{it}, produced in each country i at time t can be expressed as a function of the stochastic frontier output, $Y_{it} = Y_{it}^{*}\exp\{-u_{it}\}$, or equivalently:

$$Y_{it} = f(X_{it}, t; \beta)\exp\{v_{it}\}\exp\{-u_{it}\}, \tag{2}$$

where $u_{it} \geq 0$ is assumed to be i.i.d., with a half-normal distribution truncated at zero, $|N(0, \sigma_u^2)|$, and independent from the noise term, v_{it}.[8] Efficiency, $\exp\{-u_{it}\}$, is measured as the ratio of actual over maximum output, $\exp\{-u_{it}\} = \frac{Y_{it}}{Y_{it}^{*}}$, where $0 \leq \exp\{-u_{it}\} \leq 1$, and $\exp\{-u_{it}\} = 1$ implies full efficiency.[9]

A country is inefficient if it fails to absorb the best-practice technology. In this way, our approach is comparable to conventional, non-frontier studies (Bernard and Jones, 1996a,b; Cameron et al., 2005) that measure impediments to the absorptive capacity using TFP changes. However, in these frameworks TFP changes cannot be separated into technical change and efficiency change (Kumbhakar and Lovell, 2000). In addition, most studies assume a single technology attainable by all countries in the sample. Instead, we explicitly model the possibility of different technology regimes.

2.2. *Latent classes*

Existing literature has proposed a range of methods to tackle heterogeneity in countries' growth experiences. A common approach is to include country fixed effects and dynamic panel data analyses (Islam, 1995). Although this approach controls for differences in average growth rates, it fails to control for differences in the marginal effects of the regressors. An alternative approach identifies groups of countries with similar growth behavior - - for instance, similar income (Auerbach et al., 1994) or human capital levels (Durlauf and Johnson, 1995) or degrees of openness (Papageorgiou, 2002), or the same geographic location (Koop et al., 2000; Limam and Miller, 2004) - - and then estimates the production functions for each cluster of countries separately.

Our approach diverges from these studies in that we endogenize the classification of countries into different classes (regimes) using a latent class model. The latent class approach employs a simple parametric model to estimate regime-specific parameters

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7 For comprehensive reviews of frontier methodologies, see Kumbhakar and Lovell (2000) and Coelli et al. (2005).

8 We decompose the residual in equation (2), $\exp\{v_{it}\}\exp\{-u_{it}\}$, and identify its components, $\exp\{v_{it}\}$ and $\exp\{-u_{it}\}$, by re-parameterizing λ in the maximum likelihood procedure, where λ $(= \sigma_u/\sigma_v)$ is the ratio of the standard deviation of efficiency over the standard deviation of the noise term, and σ $(= (\sigma_u^2 + \sigma_v^2)^{1/2})$ is the composite standard deviation. The frontier can be identified by the λ for which the log likelihood is maximized (see Kumbhakar and Lovell, 2000).

9 Countries also may be inefficient if they use an input mix for which the prices of inputs are not equal to the marginal returns to these inputs. Measuring this `allocative' efficiency requires accurate input price data, which are particularly difficult to measure. Therefore, we do not consider allocative efficiency and use the term efficiency only to refer to technical efficiency.

of the model.[10] The probability that a country belongs to a particular regime can be calculated from a (multinomial logit) sorting equation and depends on observable characteristics. In line with the economic growth literature, we distinguish between four conditioning variables that may sort countries into different groups, which we specify in vector V. Human capital, openness to trade, financial development, and the share of primary sector are growth determinants that may affect factor accumulation, efficiency change, or technical change that are parameters in the frontier production model.

Human capital affects output through various channels.[11] Human capital contributes to factor augmentation. Barro (1991), for instance, argues that a significant part of the effect of human capital on growth is channeled through an increase in the investment rate for physical capital.[12] Human capital also enhances the effectiveness of the workforce, as it enhances the ability of the latter to learn, absorb, and work with new technologies created by innovation efforts, thus contributing to the absorptive capacity of the economy (Abramovitz, 1986; Benhabib and Spiegel, 1994). Furthermore, it accounts for aspects of innovation not captured by the innovation sector (e.g., R&D), including `learning-by-doing' and `on-the-job-training' (Romer, 1989; Redding, 1996). Therefore, human capital can affect the inputs of production, physical capital, and labor, as well as efficiency (through absorption of existed advanced technologies) and technical change (through innovation), which in turn influence the economic performance of a country.

Another important conduit of growth is international trade.[13] Openness to trade promotes the efficient allocation of human and capital resources through comparative advantage and increases their productivity. It further facilitates the dissemination of knowledge and technological progress.[14] In particular, exporting may involve some learning effects due to exposures to international contacts with buyers and customers. These effects likely foster knowledge and technology spillovers, such as access to technical expertise including new product designs and new production methods.[15] Imports of quality foreign capital goods also serve as a means to acquire foreign technology through reverse engineering.[16] Therefore, we include openness to trade in our analysis as a latent regime membership probability determinant.

Financial intermediaries shape the economic performance of a country by choosing which firms get to use the society's savings. A well-developed financial sector can increase the marginal productivity of capital by allocating funds to the projects for which the marginal product of capital is highest by collecting information to evaluate alternative investment projects (Greenwood and Jovanovic, 1990) and by inducing investors to invest in riskier but more productive technologies via risk sharing (Schumpeter, 1934;

[10] Throughout this paper, we use the terms `class' and `regime' interchangeably.

[11] On the effect of human capital on growth, see Nelson and Phelps (1966), Abramovitz (1986), Lucas (1988), Romer (1989), Benhabib and Spiegel (1994), and Cameron et al. (2005).

[12] This evidence receives further support from Krueger and Lindahl (2001), and Cannon (2000).

[13] Classical references include Ben-David and Loewy (1998), Edwards (1998), and Frankel and Romer (1999).

[14] These arguments are illustrated in the endogenous growth models offered by Young (1991), Grossman and Helpman (1991), and Eicher (1999).

[15] For instance, the purchase of an input requires some degree of customization or extended coordination between the seller and the buyer. Pack and Saggi (2001) develop a model in which the sellers have an incentive to provide technology to buyers, even if that technology may spill over to other sellers and buyers.

[16] When countries successfully imitate high-quality imported goods, they gain more insight into how these goods are engineered and how to improve them. Connolly (1998) discusses this `learning-to-learn' effect.

Pagano, 1993). In the absence of banks, households can guard against idiosyncratic liquidity shocks only by investing in productive assets that can be promptly liquidated, which causes them to forgo investments that are more productive but also more illiquid. This inefficiency can be considerably reduced by banks, which pool the liquidity risk of depositors and invest most of their funds in more illiquid and more productive projects. [17] Because it affects the productivity of inputs, efficiency, and technical change in an economy, we also include financial development as a latent regime membership probability determinant.

Finally, inefficient factor markets may affect the growth performance of a country. To understand why, consider dual economy effects. The marginal product of similar factors may not be equal within a country due to reallocation impediments, such as labor in an agricultural sector, which typically is less than perfectly mobile. Vollrath (forthcoming) and Temple (2005) argue that the primary sector share can affect growth in (at least) two ways. First, a large primary sector can negatively affect growth if labor productivity is low in this sector. The same influence may hold for its effect on (labor-augmenting) technical change. Second, a high primary sector share increases the effect of reallocation impediments and thereby reduces the efficiency with which countries produce. Therefore, we let a country's group membership be co-determined by sectoral structures when estimating factor shares and, more important, group-specific technical inefficiency levels. [18]

In our empirical specification, human capital (H), openness to trade (T), financial development (F), and the primary sector share (P) condition the allocation of countries to a specific regime. Within each regime, countries share the same set of parameters, as in equation (2). However, each regime also has its own set of parameters. Note that conditioning group membership on this vector V affects *all* parts of the growth decomposition for three reasons. First, countries are now compared to the frontier of 'their' estimated peer group and thus likely to be more efficient compared to a single frontier approach. Second, factor elasticities of both capital and labor will be different since the slope of regime-specific production frontiers will differ in V too. Third, each frontier can now shift at their own pace, thereby allowing for different technical change per regime. To estimate equation (2) we must specify the functional form of the production frontier. Specification tests favor a translog specification production function. [19] In turn, for a translog specification with a general index of technical change specified by means of time dummies D_t (see Baltagi and Griffin, 1988) and regimes $z(=1,..,Z)$, we can write a latent class stochastic frontier as:

$$\begin{aligned}\ln Y_{it} &= \beta_z + \beta_{1|z}\ln K_{it} + \beta_{2|z}\ln L_{it} + \tfrac{1}{2}\beta_{11|z}\ln K_{it}^2 + \tfrac{1}{2}\beta_{22|z}\ln L_{it}^2 \\ &\quad + \beta_{12|z}\ln K_{it}\ln L_{it} + \gamma_{t|z}D_t + \delta_{kt|z}\ln K_{it}D_t + \delta_{lt|z}\ln L_{it}D_t + v_{it|z} - u_{it|z},\end{aligned} \tag{3}$$

[17] For empirical evidence, see King and Levine (1993), Easterly (1999), and Beck et al. (2000), among others.

[18] We thank the editor for suggesting the primary sector share as a latent regime membership probability determinant.

[19] We test whether a translog is preferable to a Cobb-Douglas specification, which appears in most prior literature. Our tests (see Section 4.1) support a translog specification. Estimations of specifications with more flexible functional forms (Fourier Flexible) suffered from multicollinearity problems.

To operationalize equation (3), we must allocate each observation *it* to a regime z. This is done by first making the contribution of each observation to the likelihood function conditional on its regime membership. The unconditional likelihood then can be averaged over the latent classes using the prior probability of membership in a class (regime) as weights of the membership in class z.

In our conditional latent class frontier model, regime membership probability conditional on the vector V (consisting of the four conditioning variables, H, F, T, and P) determines regime membership. Greene (2005) shows these conditional probabilities can be estimated using a multinomial logit model:

$$\theta_{it} = \frac{\exp(V_{it}\theta_z)}{\Sigma_{z=1}^{Z} \exp(V_{it}\theta_z)}, \tag{4}$$

where θ measures the odds of belonging to regime z, conditional on the values of the set of conditional variables V_{it}.

The resulting system of equations (3) and (4) is estimated by maximizing iteratively back and forth between posterior group probabilities from equation (4) and the (weighted) log-likelihood function used to estimate equation (3).[20] The likelihood maximization in equation (3) depends not only on inputs and outputs per industry but also on efficiency (λ and σ). Therefore, in contrast to *a priori* clustering on the basis of some individual proxy, both the technology parameters β and efficiency u can be determined endogenously through latent sorting into Z classes.

In summary, we redefine the production frontier as a latent class frontier characterized by a system of equations: Z stochastic production frontiers and a multinomial logit model with conditioning variables (human capital, openness to trade, financial development, and the primary sector share) that accounts for the sorting (of countries) into each of the Z regimes.

An important feature that distinguishes our modeling approach from previous latent class studies (Greene, 2002a,b, 2005; Orea and Kumbhakar, 2004) is that we allow countries to switch regimes over time. For our sample of 77 countries observed over a maximum of thirty-one years, we define six different time periods: 1970-1974, 1975-1979, 1980-1984, 1985-1989, 1990-1994, and 1995-2000. Equations (3) and (4) are estimated on annual data, and observations for some years may be missing. *Within* each period, observations per country are not independent because the country must fall within one of the regimes during that period, and the probability of being in a regime depends on the average of the variables used to estimate regime membership.[21] However, *across* periods, observations on a single country are treated as independent. For example, in moving from $t = 5$ (the last year of the period 1970-1974) to $t = 6$ (the first year of the period 1975-1979), a country is treated as a different i in our panel dimension *it* and can

[20] The likelihood function is $LF(i,t|z) = f(Y_{it}|K_{it}, L_{it}, t; \beta_z, \delta_z, \sigma_z, \lambda_z) = \frac{\Phi(\lambda_j \epsilon_{it|z})}{\Phi(0)} \frac{1}{\sigma_z} \phi\left(\frac{\epsilon_{it|z}}{\sigma_j}\right)$, where $\epsilon_{it|z} = Y_{it|z} - f(K_{it|z}, L_{it|z}, t; \beta_z)$, $\lambda_z = \frac{\sigma_{u|j}}{\sigma_{v|z}}$, $\sigma_z = \sqrt{\sigma^2_{u|z} + \sigma^2_{v|z}}$, and ϕ and Φ are the probability density and cumulative distribution functions of standard normal distribution, respectively (see Greene, 2005).

[21] In this modeling approach the allocation of a country in a regime in a specific period depends on the period averages of the conditioning variables. We consider this to be in line with theory, as we expect the allocation of a country in, for example, the period 1990-1994 to depend on the average level of human capital (and the other conditioning variables) in that period, rather than the initial level in 1970.

switch regimes.

The advantage of this approach is that a country can be in one regime in one period and in another regime next period. [22] As a result, the regime allocation of a country is not restricted, and a country's allocation in a given period is independent of its allocation in other periods. This flexibility adds an important dimension to our analysis of the components of countries' growth in that we can study regime migrations. We turn next to decomposing output growth for different regimes.

2.3. *Decomposing Output Growth*

A key aim of this paper is to relate our results to some of the major macroeconomic debates about why and how some countries grow faster than others. We therefore decompose output growth for each regime into three components: input growth, represented by movements along the frontier; technical growth, reflected by shifts of the production frontier; and efficiency growth, captured by movements toward (or away from) the production frontier as countries absorb and implement best practice technologies and reduce (or increase) technical inefficiencies.

We take logs and totally differentiate equation (2) with respect to time, which yields a convenient expression of output growth for every regime, z:

$$gr(Y_{it}) = \frac{\dot{Y}_{it}}{Y_{it}} = \frac{\partial \ln f_{it}}{\partial t} - \frac{\partial u_{it}}{\partial t} + \epsilon^K_{it}\frac{\dot{K}_{it}}{K_{it}} + \epsilon^L_{it}\frac{\dot{L}_{it}}{L_{it}}, \tag{5}$$

where ϵ^K_{it} and ϵ^L_{it} denote the partial elasticity of the stochastic frontier output with respect to the inputs, physical capital and labor, respectively, and the dotted variables refer to time derivatives. [23]

The first term, $\frac{\partial \ln f_{it}}{\partial t}$, corresponds to technical growth, TC_{it}=$\frac{\partial \ln f_{it}}{\partial t}$, where $TC_{it} > 0$ indicates an upward shift of the production frontier (technical progress). Technical change can be attributed to capital change (TC^K_{it}) or labor change (TC^L_{it}), or it may be independent of the inputs in the form of pure technical change (TC^P_{it}). The second term, $-\frac{\partial u_{it}}{\partial t}$, corresponds to efficiency change, EC_{it}=$-\frac{\partial u_{it}}{\partial t}$, where $EC_{it} > 0$ represents a reduction in inefficiency. Because we allow inefficiency to vary freely over time, the time evolution of our efficiency term is not captured by a specific functional form (see Jondrow et al., 1982). We approximate $\frac{\partial u_{it}}{\partial t}$ by the growth rate of u_{it} over time ($\frac{u_{it}-u_{it-1}}{u_{it-1}}$). The last two terms, $\epsilon^k_{it}\frac{\dot{K}_{it}}{K_{it}} + \epsilon^l_{it}\frac{\dot{L}_{it}}{L_{it}}$, capture the input change, IC_{it}=$IC^K_{it} + IC^L_{it} = \epsilon^k_{it}\frac{\dot{K}_{it}}{K_{it}} + \epsilon^l_{it}\frac{\dot{L}_{it}}{L_{it}}$. The input change can vary for two reasons: pure factor accumulation or changes in input factor elasticities. For example, if a country exhibits constant returns to scale, changes in the level of input factors do not influence the rate of change of output growth. If labor

[22] Orea and Kumbhakar (2004) also propose a latent class frontier model. The subtle difference between the models of Greene (2002a,b, 2005) and that of Orea and Kumbhakar (2004) is described by Orea and Kumbhakar (2004, p. 172). In the latter, the log density (likelihood function) for an individual (or a country, here) is defined as the same over all time periods in the model. In contrast, it defined for each individual at each time t in Greene's (2002) model. To allow countries to switch regimes, we use the latent class model specified by Greene (2002a,b, 2005).

[23] For clarity, we delete the latent regime subscript z in this section.

exhibits, for example, increasing returns to scale $\left(\frac{\partial \ln f(K,L,t;\beta)}{\partial \ln L_{it}}\right) > 1$, an increase in the labor force $(\frac{\dot{L}_{it}}{L_{it}}) > 0$ further increases the rate of change of output growth.

Table 1
Decomposition of Output Growth

$\frac{\dot{Y}_{it}}{Y_{it}}$	=	$TC_{it} + EC_{it} + SC_{it}$
TC_{it}	=	$TC_{it}^{P} + TC_{it}^{K} + TC_{it}^{L}$
	TC_{it}^{K} =	$\delta_{kt} \ln K_{it}$
	TC_{it}^{L} =	$\delta_{lt} \ln L_{it}$
	TC_{it}^{P} =	γ_t
EC_{it}	=	$-\frac{u_{it}-u_{it-1}}{u_{it-1}}$
IC_{it}	=	$SE_{it}^{K} + SE_{it}^{L}$
	IC_{it}^{K} =	$\epsilon_{it}^{k} \frac{\dot{K}_{it}}{K_{it}}$, where $\epsilon_{it}^{K} = \beta_1 + \beta_{11} \ln K_{it} + \beta_{12} \ln L_{it} + \delta_{kt} D_t$
	IC_{it}^{L} =	$\epsilon_{it}^{l} \frac{\dot{L}_{it}}{L_{it}}$, where $\epsilon_{it}^{L} = \beta_2 + \beta_{22} \ln L_{it} + \beta_{12} \ln K_{it} + \delta_{lt} D_t$

Table 1 summarizes the output growth decomposition for every regime,z, based on the production function specified in equation (3).

3. Data

Our sample consists of 77 countries over the period 1970-2000. The countries included in our sample are listed in Table A.3 in the Appendix. Annual data are retrieved from various sources. Output (Y), measured as real gross domestic product (GDP), is constructed from the Penn World Tables, version 6.1 (PWT 6.1), by taking the product of the real per capita GDP, measured in 1996 international purchasing power parity (PPP) dollars (chain index) and the national population numbers. Labor force (L), measured in millions, is also taken from the Penn World Tables. The computation of capital stock (K) series, in 1996 international PPP dollars, follows the perpetual inventory method in Hall and Jones (1999).[24]

To estimate the number of regimes and respective membership probabilities, we rely on four conditioning variables commonly used in the economic growth literature. Data on human capital (H), measured as the average years of education of the population that is at least 25 years old, are retrieved from Barro and Lee (2001).[25] Openness to trade (T), measured as the sum of exports and imports relative to GDP, is obtained from the World Bank World Development Indicators (2006). From the same data source,

[24] We use a depreciation rate of 6% and the average growth over the first ten years to determine a country-specific average growth rate. For robustness we also calculate a backward-looking capital stock using data from 1960 onwards. The results are qualitatively similar. Our capital stock series has wider coverage than the PWT 6.1 variable for capital stock per worker, which is only available for 62 countries after 1965. When the two series overlap, the correlation coefficient between their log levels is 0.97.

[25] Workers in different countries have different levels of skills. Typically, these skills develop through education and experience. The lack of data about the latter prompts us to measure education according to the years of schooling embodied in the labor force. Given missing annual data, we use a linear interpolation per year. Assuming that human capital is constant per five-year period does not change the results qualitatively.

Table 2
Descriptive statistics

	Mean	Std. Dev.
Output (Y)	250.332	737.888
Capital (K)	69.429	221.566
Labor (L)	16.474	42.174
Human capital (H)	5.444	2.834
Openness to trade (T)	62.730	38.574
Financial development (F)	38.072	27.610
Primary sector share (P)	13.768	11.972

There is 1,913 observations for 77 countries between 1970 and 2000.

we retrieve the primary sector share (P) relative to total GDP. Finally, as a proxy for financial development (F), we use the amount of deposits held in the financial system as a percentage of GDP provided in Beck et al. (2000). [26] Table 2 contains the descriptive statistics.

4. Results

First, we examine whether there is a single production function. That is, we test whether there is one universal model that can adequately describe the growth experience of all countries. Second, we present a tripartite output growth decomposition for countries with similar growth experiences, according to their identified regime. We relate these results to macroeconomic debates about whether input accumulation or productivity drives output growth and to the convergence hypothesis.

4.1. *Is There a Universal Production Function?*

We start by investigating whether countries in our sample can be described by a common production function. In estimating the latent class frontier model defined by equations (3) and (4), we first must determine the number of regimes, Z. Multiple regime endogenous growth models (Azariadis and Drazen, 1990; Kejak, 2003) merely suggest the possibility of multiple steady states or growth regimes, without being explicit about the exact number of regimes. Without theoretical guidance into the `optimal' number of regimes, we must rely on statistical methodologies. We determine the number of regimes in our preferred specification by following the suggestions provided by Orea and Kumbhakar (2004) and Greene (2005).

We formally test for the optimal number of regimes, Z, using log-likelihood ratio tests and the Akaike and Schwartz Bayesian information criteria (AIC and $SBIC$, respectively), as we outline in Table A.1 in the Appendix. The preferred specification has the highest log-likelihood value and the lowest AIC or BIC values. The test results in Table A.1 favor a specification with three regimes over those specifications with two. [27]

[26] See Beck et al. (2000) on February 21, 2006.

[27] Three is a maximum number of regimes at which neither multicollinearity nor over specification prohibit convergence of the maximum likelihood estimator. An unconditional three-regime specification without fur-

Hence, our conditional latent class model defined by equations (3) and (4) supports the existence of three regimes.[28]

Table 3 below contains the estimated parameters for the translog production function with a time trend (top panel), efficiency parameters (middle panel) and membership probability parameters (bottom panel) for each of the three regimes we identify: emerging (A), mature (B) and developing (C). Before explaining in subsequent sections in greater detail the growth process and further characteristics that give rise to this taxonomy, we test whether the parameter estimates differ significantly across regimes using Wald tests for joint equality across regimes (A, B and C) (see the top panel of Table A.2 in the Appendix). Low p-values less than 1% demonstrate that parameters are jointly significantly different across the three regimes.

However, statistically significant differences for the parameters in the production function are insufficient to assess whether the specification of multiple regimes with their own production frontiers is important for analyzing the output growth of countries. The middle panel of Table 3 shows that inefficiency matters too. For regime C, the efficiency parameter, λ ($= \sigma_u/\sigma_v$, the ratio of the standard deviation of efficiency over the standard deviation of the noise term), is 2.053 and significant at the 1% level. As such, inefficiency is approximately twice as great as noise in this regime. The same result holds for regime B, where inefficiency is one-and-a-half times times the size of noise (λ is 1.525) and significant at the 1% level. In regime A, however, the production process is fully efficient, as exemplified by the insignificance of λ.

Finally, the bottom panel of Table 3 demonstrates the importance of the conditioning variables. The use of a multinomial logit specification implies an estimation of membership likelihood relative to the reference group, or regime C here. Financial development, primary sector share, and openness to trade have significant effects on the probability of belonging to regime A. For regime B human capital, primary sector share, and openness to trade are significant. For example, an increase in financial development (human capital) of 1% increases the probability of belonging to regime A (B) by 1.04% (1.53%).[29] Wald tests (see the bottom panel of Table A.2 in the Appendix) show that the joint effect of a change in all four regime determinants on the probability of belonging to regime A differs from its effect on the probability of belonging to regime B. However, the coefficients for human capital and the primary sector share are not significantly different between regimes A and B. Financial development, in turn, is critical distinguishing between regimes A and B. The effect of financial development on regime A membership is both higher and more significant. These results confirm the importance of the *mix* of regime determinants. Individual determinants (e.g., financial development) may be im-

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ther group determinants Z is rejected, as are the Cobb-Douglas and translog specifications with a linear time trend. These results are available on request.

[28] In response to comments of an anonymous referee, we also specified a latent class model with the conditioning vector, V, as part of the deterministic kernel of the latent class model, similar to some cross-country growth regression literature in which explanatory variables such as human capital, openness to trade, and financial development enter directly into the production function. Just as the additional interaction of time and squared terms discussed before, this specification suffers from over identification, multicollinearity, and convergence problems and therefore cannot be estimated.

[29] We calculate probabilities by taking the exponent of the coefficients from the bottom panel of Table 3.

Table 3
Latent class frontier estimation results

Regime	*A*		*B*		*C*	
Variable	coeff.		coeff.		coeff.	
Latent technology regime parameters						
Constant	-0.669	(0.106)***	-0.334	(0.019)***	-1.015	(0.150)***
$\ln K$	0.471	(0.012)***	0.394	(0.011)***	0.403	(0.056)***
$\ln L$	0.659	(0.017)***	0.579	(0.017)***	0.204	(0.075)***
$\ln K^2$	-0.050	(0.005)***	0.036	(0.005)***	0.024	(0.015)***
$\ln L^2$	-0.124	(0.007)***	0.000	(0.008)	0.279	(0.016)***
$\ln K \times \ln L$	0.060	(0.006)***	0.018	(0.006)***	-0.065	(0.012)***
D_2	0.681	(0.034)***	0.098	(0.022)***	0.373	(0.145)***
D_3	0.439	(0.030)***	0.338	(0.023)***	0.195	(0.151)
D_4	0.599	(0.031)***	0.194	(0.023)***	-0.141	(0.159)
D_5	0.446	(0.031)***	0.243	(0.024)***	0.163	(0.154)
D_6	0.679	(0.034)***	0.207	(0.025)***	0.093	(0.148)
$\ln K \times D_2$	0.031	(0.012)***	0.103	(0.014)***	0.081	(0.043)**
$\ln K \times D_3$	0.032	(0.017)**	0.133	(0.015)***	-0.011	(0.046)
$\ln K \times D_4$	0.214	(0.016)***	0.169	(0.014)***	-0.120	(0.055)***
$\ln K \times D_5$	0.140	(0.014)***	0.185	(0.016)***	-0.210	(0.061)***
$\ln K \times D_6$	0.168	(0.015)***	0.147	(0.016)***	-0.190	(0.064)***
$\ln L \times D_2$	-0.159	(0.018)***	-0.222	(0.020)***	-0.088	(0.075)
$\ln L \times D_3$	-0.030	(0.024)	-0.350	(0.021)***	0.118	(0.075)
$\ln L \times D_4$	-0.325	(0.022)***	-0.372	(0.020)***	0.238	(0.082)***
$\ln L \times D_5$	-0.172	(0.019)***	-0.442	(0.023)***	0.031	(0.077)
$\ln L \times D_6$	-0.295	(0.020)***	-0.369	(0.020)***	0.213	(0.075)***
Efficiency parameters						
σ	0.115	(0.004)***	0.139	(0.008)***	0.275	(0.020)***
λ	0.011	(1.119)	1.525	(0.282)***	2.053	(0.469)***
Regime membership probability parameters						
Constant	3.276	(1.085)***	2.528	(1.079)***	- reference group -	
Human capital	0.176	(0.158)	0.425	(0.157)***	- reference group -	
Financial development	0.039	(0.016)***	0.022	(0.016)	- reference group -	
Primary sector share	-0.095	(0.025)***	-0.094	(0.025)***	- reference group -	
Openness to trade	-0.031	(0.006)***	-0.027	(0.006)***	- reference group -	
Observations	689		919		305	

Standard errors in parentheses; the data refer to 1,913 observations on 77 countries over the period 1970-2000; D_k, k = 2, 3, 4, 5, and 6 are time dummies for the periods 1970-74, 1975-79, 1980-84, 1985-89, 1990-94, and 1995-2000, respectively; $\sigma\ [= (\sigma_u^2 + \sigma_v^2)^{1/2}]$ and $\lambda [= \sigma_u/\sigma_v]$ are efficiency parameters; the log-likelihood value is 1,119.540; significance at the 10/5/1 % levels (*/**/***).

portant, but the interaction between regime determinants is especially crucial to identfy relevant peer groups of countries.

To explore differences among the three regimes further, we present each regime's factor elasticities, ϵ_{it}^K and ϵ_{it}^L, technical efficiency estimates, u_{it}, and the marginal rate of technical substitution, $MRTS$, in Table 4.

Table 4
Factor elasticities, efficiency, and marginal rate of technical substitution

	Regime A		*Regime B*		*Regime C*	
Capital elasticity (ϵ_{it}^{K})	0.570	(0.086)	0.658	(0.116)	0.255	(0.119)
Labor elasticity (ϵ_{it}^{L})	0.396	(0.160)	0.299	(0.114)	0.556	(0.326)
Technical efficiency (u_{it})	0.999	(0.000)	0.953	(0.024)	0.898	(0.058)
MRTS	2.198	(3.182)	2.500	(0.874)	0.699	(10.060)
Observations	689		919		305	

There is 1,913 observations for 77 countries over the period 1970-2000. All calculations are based on latent class-specific parameter estimations evaluated at the mean. Standard deviations in parentheses. *MRTS* is the marginal rate of technical substitution, calculated as the ratio of scale elasticity-adjusted capital to labor change.

As Table 4 clearly shows, there are differences between regimes *A* and *B* on the one hand and regime *C* on the other. The latter regime, which is the smallest in terms of number of observations, has all the characteristics of a less developed regime. Average inefficiency is more than 10%, and the productivity of capital, as measured by the capital elasticity (ϵ_{it}^{K}) is less than half that of the other regimes, in line with a very low marginal rate of technical substitution. Regime *A* exhibits the highest labor elasticity and is almost 100% efficient. Capital elasticity is highest in regime *B*, which also has the highest marginal rate of technical substitution. The differences in factor elasticities across regimes are also statistically significant, as shown in the middle panel of Table A.2 in the Appendix.

The relatively lower values of elasticities of capital and labor in regime *C* can be explained in conjunction with Table 3. Regime *A* has the highest level of financial development, whereas regime *B* exhibits the highest level of human capital, as the bottom panel of Table 3 shows. More human capital and a better developed financial system should contribute to the productivity of capital and labor and therefore increase the probability of that country belonging to a regime with higher capital or labor elasticity. The average values for these conditioning variables confirm the status of the lesser developed regime *C*, which is characterized by a low level of human capital and financial development.

More pronounced differences exist between the primary sector share of regimes *A* and *B* compared to regime *C*. The share of the relatively unproductive and often inefficient agricultural sector (Vollrath, forthcoming) is the highest in regime *C*. A high share of this relatively unproductive sector increases the probability that a country in such a regime exhibits low productivity of capital and labor due to existing inefficiencies. Regime *C* is also characterized by a high openness to trade and the association of this trait with lower elasticities of labor and capital supports some existing concerns about the benefits of openness to trade for developing countries. If market or institutional imperfections exist, such openness actually can lead to under-utilization of human and capital resources, concentration in extractive economic activities, and specialization away from technologically advanced increasing-returns sectors (Grossman and Helpman, 1991; Sachs and Werner, 1999; Rodriguez and Rodrik, 2001). Therefore, it is not surprising that the (least) developed economies in regime *C* exhibit low productivities of capital and labor.

Estimates in Table 4 also reveal significant heterogeneity in the elasticities of inputs across regimes. We find almost constant returns to scale in all regimes, as most of cross-country regressions assume when examining growth differentials (Mankiw et al., 1992). However, in regime *C* capital elasticity is lower than labor elasticity, which contrasts with results from the growth empirics literature that reports a marginal product of capital as high as 0.60 (Mankiw et al., 1992). Furthermore, efficiency levels are statistically significant and different for every regime. Overall, we conclude that there is no average or representative country. Also, all countries do not operate at the fully efficient production frontier. Instead, we find different regimes of countries, each with its own specific characteristics. Rather than merely assigning countries to groups, we find support for using the four conditioning variables jointly to determine the allocation of a country to regimes *A*, *B*, or *C*.

Another distinctive feature of our model is the possibility that a country may change regimes over time. This raises the question if and how often countries do change membership over time. We depict regime migrations in Table 5 including the frequency and absolute number of regime allocation changes between any two time periods. [30] While the migration pattern observed may appear rather dynamic, imposing regime stickiness by not permitting regime switches implied counter-intuitive country groupings in an earlier version of this paper, presumably reflecting changing technology and group determinants. We prefer here to permit countries to follow different growth processes due to regime switches similar in spirit to Jerzmanowski (2006), rather than imposing the rigid assumption of unique equilibrium growth per country.

Most observations are located on the diagonal of Table 5, which indicates that overall countries appear to change relatively rarely in terms of their production structure. At the same time, especially for countries in regimes *A* and *B* a stable group allocation seems difficult. Different technology regimes appear to be relevant for some countries' growth processes at different times. We checked if some countries are `borderline' cases in the sense that our model allocated them to regimes *A* or *B* with a conditional probability that is close to 50%, the conventional cut-off level in the multinomial logit model of equation (4). However, the conditional probability of group membership is very high in almost all cases. In fact, it is above 90% for more than 90% of the sample. Hence, the relatively high frequency of regime switches between regimes *A* and *B* is not the result of our model's flexibility.

This active migration pattern across technology regimes is to some extent in line with Jerzmanowski (2006). Using a Markow-regime switching model, he notes that almost all countries in his sample `visit' each of the growth regimes identified there on the basis of output-per-worker growth dynamics alone. In this sense, the frequency of migrations we observe does not seem excessive. It is also important to note that most migrations between the two fairly developed technology regimes *A* and *B* involve countries that switch back and forth (see also Table A.3). Of the 79 (42+37) switches between regimes *A* and *B*, approximately 60% pertain to countries that change back and forth. [31] Put differently, 36 out of 42 moves from *A* to *B* (27 out of 37 from *B* to *A*) are accounted for by the same countries, which may simply be hard to classify. In line with Jerzmanowski (2006), we also find that regime migrations are rarely a viable strategy to escape poverty traps, since exiting the worst performing regime *C* for good is rare. Most extreme up-

[30] Since we distinguish six episodes, we have five migration matrices but display only the aggregate, unconditional migration probabilities.

[31] Finland and Trinidad & Tobago migrate in and out of these two regimes a total of three times.

grades from regime C to A are followed either by gradual (for example Rwanda) or straight (for example Togo) `downgrades' back to the regime C. Finally, as shown in the last column of Table 5, few countries move from regimes A and B to regime C.

Table 5
Migration matrix

		To regime			
		A	*B*	*C*	Total
	A	54.37	40.78	4.85	100
		(56)	(42)	(5)	(103)
	B	26.24	72.34	1.42	100
From regime		(37)	(102)	(2)	(141)
	C	17.02	12.77	70.21	100
		(8)	(6)	(33)	47
	Total	34.71	51.55	13.75	100
		(101)	(150)	(40)	(291)

Numbers denote the percentage probability of moving from regime to another. The number of countries per cell appears in parentheses.

A natural question that arises at this point pertains to which countries belong to which regime and how plausible the allocations are. Table A.3 in the Appendix provides a list of the countries and shows regime memberships for each of the six periods across which they are permitted to switch regimes. Each country in our sample in each period joins the regime for which it has the highest conditional probability. Most countries belong to either one or two regimes over the entire sample period. Regime B is the most populated followed by regime A.

To confirm the plausibility of our classification, we provide Table 6, which shows the difference between the subjective and objective probabilities of being a regime member. The subjective probability is the ratio of the number of years a country has been a member of a regime to the total number of years it appears in the sample. The objective measure is calculated as the product of the number of years a country appears in the sample and the relative size of the regimes (e.g., 689/(689+919+305) for regime A). We calculate both probabilities *after* determining the regimes. A positive number in Table 6 indicates that countries from a certain region are *more* likely to be members of a regime than if the regions were randomly distributed across regimes. [32]

The evidence in Table 6 shows that geography matters. Our classification justifies, to a certain extent, the regional classification argument (countries in the same geographical region may have similar endowments, such as natural resources). Asian countries are most likely to be members of regime A, whereas regime B is very likely to contain European countries. All regions are underrepresented in the labor-intensive and inefficient regime C, with the notable exception of Africa (mainly sub-Saharan countries). A few Asian and Latin American countries, such as Pakistan, Indonesia, and Honduras, are also allocated to regime C, but they eventually exit this worst performing regime

[32] We exclude Oceania from the table due to few observations.

Table 6
Do geography and income matter?

Region	*Regime A*	*Regime B*	*Regime C*
Africa	-0.102	-0.283***	0.385***
Americas	0.044	0.060	-0.104**
Asia	0.239**	-0.162*	-0.077*
Europe	-0.073	0.215***	-0.142***
Income level			
Output per capita	15.749(12.480)	17.977(13.885)	3.048(5.156)

Numbers refer to the differences between the conditional and unconditional probabilities of being a regime member. Differences between conditional and unconditional probabilities are tested using a two-sided t-test. Significance at the 10/5/1% levels (*/**/***).

and enter either regime A or B. In addition, we find some evidence in favor of the importance of similar production structures (countries with similar level of development, such as income per capita, may have similar structures of production). Table 6 shows that high-income countries (e.g., European, and the United States) tend to be members of regime B, medium-income countries (e.g., Asian nations) often appear in regime A, and low-income countries (e.g., African nations) are mostly in regime C.

Our classification can therefore, to some extent, be compared with studies that apply similar methodologies (e.g., stochastic frontier analysis) but base their country allocation *ex ante* on geography (Koop et al., 2000; Limam and Miller, 2004). However, in every region some countries may behave very differently from other countries in the same geographical region. For example, as Davis et al. (2007) argue, purely based on geography, the Philippines would be placed with other countries in East Asia, although its development is much more akin to that of many Latin American countries. This observation is supported by our classification. Other studies, for example, Paap et al. (2005) and Davis et al. (2007), use latent class analysis and allocate countries based on multiple conditioning variables, in line with our approach. However, these studies do not consider the possibility that countries can move over time to a more (less) advanced regime, which is a realistic scenario.

In summary, three main findings emerge from our analysis so far. First, all countries do not follow a common growth process, nor is the growth process of any country entirely unique. Instead, we find three distinct growth processes or, equivalently, three growth regimes. In addition, we find that some countries over time improve (or deteriorate) their production and move to a more (less) advanced regime.

Second, (in)efficiency, which has been widely ignored by conventional growth empirics, is statistically important in our study and quantitatively different across regimes. We find that countries from regime A are fully efficient, whereas the least efficient countries appear in regime C. This division implies that development policies for some countries geared toward a better exploitation of existing technologies, rather than augmenting new ones, may be beneficial.

Third, membership in a certain regime depends on the joint effect of multiple factors - - namely, human capital, openness to trade, financial development, and primary sector share. Our results clearly show that no single factor can explain the allocation of countries to a certain regime.

To shed more light on the growth experience of the three regimes, especially the quite `similar' regimes *A* and *B*, we turn next to the decomposition of output growth for every regime.

4.2. *How Do Countries Grow?*

Having identified the number of regimes and their characteristics, we next consider how countries in each regime grow. Therefore, we decompose output growth per regime into three components: input growth, technical growth, and efficiency growth, as in equation (5). To allow for potential heterogeneity in growth patterns within regimes, we identify high-, medium,- and low-growth countries according to the 33rd and 66th percentiles of the overall growth distribution as cut-off points in each regime. In Table 7 we present the break down of countries in each regime according to their growth performance. Figure 1 graphically presents a more detailed decomposition of technical change and factor accumulation.

Table 7
Output growth decomposition

	Regime A							
	High		*Medium*		*Low*		*Total*	
$gr(Y_{it})$	0.309	(0.193)	0.075	(0.038)	-0.108	(0.085)	0.123	(0.227)
TC_{it}	0.217	(0.194)	0.012	(0.039)	-0.170	(0.091)	0.055	(0.220)
EC_{it}	0.003	(0.012)	0.002	(0.011)	0.004	(0.020)	0.003	(0.015)
SC_{it}	0.067	(0.029)	0.061	(0.023)	0.057	(0.023)	0.063	(0.026)
N	325		161		203		689	
	Regime B							
	High		*Medium*		*Low*		*Total*	
$gr(Y_{it})$	0.210	(0.069)	0.058	(0.036)	-0.069	(0.077)	0.042	(0.120)
TC_{it}	0.123	(0.086)	-0.003	(0.040)	-0.124	(0.090)	-0.018	(0.119)
EC_{it}	-0.001	(0.013)	0.000	(0.015)	-0.004	(0.022)	-0.002	(0.018)
SC_{it}	0.073	(0.023)	0.061	(0.018)	0.059	(0.024)	0.063	(0.022)
N	211		371		337		919	
	Regime C							
	High		*Medium*		*Low*		*Total*	
$gr(Y_{it})$	0.302	(0.126)	0.069	(0.036)	-0.157	(0.158)	0.136	(0.222)
TC_{it}	0.225	(0.153)	0.017	(0.050)	-0.191	(0.158)	0.085	(0.217)
EC_{it}	0.008	(0.042)	0.004	(0.030)	-0.003	(0.051)	0.004	(0.042)
SC_{it}	0.047	(0.031)	0.048	(0.026)	0.037	(0.032)	0.045	(0.030)
N	165		74		66		305	

Standard errors in parentheses. High growth > 66th percentile of the total growth distribution. Low growth < 33rd percentile of the total growth distribution. *N* is the number of observations in each regime. Variables are as defined in Table 1.

In the comparison of regime *B* with regime *A* in Section 4.1, we noted that the differences between their conditioning variables and their coefficients appeared marginal. However, we cautioned against a comparison of individual variables and coefficients and emphasized the multivariate effect of the conditioning variables. We confirm this latter point by realizing that output growth decomposition in Table 7 is markedly different for each regime.

We identify regime A as the emerging regime, which contains many Asian countries and has the most productive labor among all regimes as well as a relatively high level of financial development and human capital that is somewhat lower than that for countries in regime B. The output growth decomposition in Table 7 also reveals that countries in regime A grow primarily as a result of factor accumulation and technical change. [33] As Figure 1 shows, the former effect consists predominantly of capital accumulation, whereas the latter influence consists mostly of pure technical change (especially in the high-growth countries in this regime). These results confirm the importance of financial development in facilitating capital accumulation, through both domestic savings and foreign capital (Pagano, 1993) as well as in reallocating capital to firms that generate the greatest technical change (Schumpeter, 1934). Efficiency change is positive but very small in this highly efficient regime.

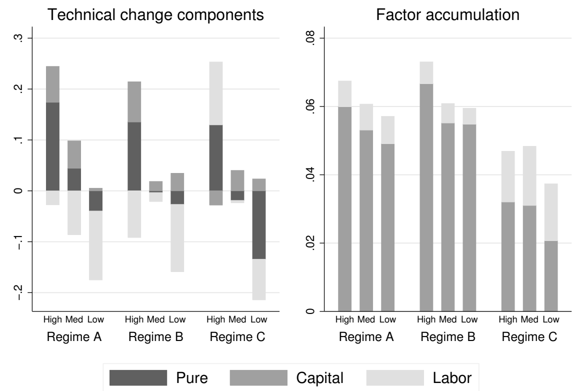
We can relate these findings about regime A to the ongoing debate about the sources of the impressive output growth performance of some East Asian countries. Some studies (Young, 1994) argue that East Asian countries grow primarily through factor accumulation, whereas others (Pack and Page, 1994) point to the role of the productivity of inputs. Our results suggest that factor accumulation is important but technical change is a key factor overall, especially for high-growth countries.

Regime B is the mature regime, which contains many European countries and the United States, has the highest output per capita, indicates an important role for human capital, and achieves the highest capital elasticity of all regimes. Output growth for countries in this regime is driven by factor accumulation, especially through increases in the capital stock. Such increases may result from a high human capital stock, which increases the rate of of investment (Barro, 1991; Krueger and Lindahl, 2001; Sianesi and Reenen, 2003). The regime is also characterized by negative technical change, largely due to labor-augmenting technical regress, as we show in Figure 1. The main explanation for the negative technical change in the low-growth subsample of regime B is the (temporary) migration of countries from regimes A and C (e.g., South Africa and Indonesia) to regime B. The same is true for the small negative efficiency change.

Finally, we characterize regime C as the developing regime. It contains many African countries, with very low output per capita, a high degree of openness to trade, and a large primary sector share. Output growth for these countries results from technical change, efficiency change, and factor accumulation. The latter is fairly modest and involves both capital and labor accumulation. Technical and efficiency change are important, but as Table 7 shows, they have the greatest effect on high-growth countries. From Figure 1, we observe that technical change in high-growth countries in this regime is both pure and labor augmenting. In contrast, low-growth countries in the developing regime experience both pure and labor augmenting technical regress, which implies an inward shift of their production possibility frontier. The latter may initially seem odd.

[33] Some low-growth countries in this regime exhibit technical regress. For example, Brazil exhibits technical regress in the early 1990s. Since 1989 was the first presidential election after twenty-nine years of military rule, technical regress may reflect the burden of setting these decades of economic mismanagement straight.

Figure 1. Mean output growth components of technical change and factor accumulation



Components as defined in Table 1. Output growth on y−axis in percentages.

However, the 66 observations in this low-growth sub-sample include primarily observations of Uganda and Rwanda in the early 1990s (which were marked by various conflicts in The Great Lakes region), Congo at the end of the same decade (the time of the Second Congo War), Zambia (during 1986-1994 when it suffered one of the highest debt burdens due to the collapse in the price of copper), and other sub-Saharan countries in Africa that have suffered from various political, health, and/or natural disasters during these years. Both the group allocation of our model and the implication of the actual destruction of some economies' production possibilities thus seems logical.

Recall that the share of the relatively unproductive and often inefficient agricultural sector (Vollrath, forthcoming) is the highest in regime *C*. The negative relationship between output per capita and primary sector share across our regimes may reflect a dual economy reallocation problem (Vollrath, forthcoming; Caselli, 2005). Labor in the agricultural sector, which tends to be less than perfectly mobile, may lead to factor market misallocations that seriously hamper growth if labor productivity in this sector falls too low.

Regime *C* is also characterized by a high degree of openness to trade, which should contribute positively to growth such as through the knowledge spillovers from importing and exporting (Edwards, 1998; Ben-David and Loewy, 1998; Frankel and Romer, 1999). However, the effects of trade on growth depend on the composition of exports in particular. Hausmann et al. (2007) develop an index that measures the `quality' of countries' export baskets and provide evidence that only countries that produce and export high-productivity goods perform better in terms of growth. Imports only enhance growth when they include high-quality foreign capital goods, which embody advanced foreign technology, and when an adequate level of human capital exists to perform reverse engineering and possibly improve on the imported technology (Connolly, 1998). These two conditions rarely can be met in low-income, developing countries. Furthermore, with market or institutional imperfections, openness can lead to the underutilization of resources, concentration in extractive economic activities, or specialization away from technologically advanced, increasing-returns sectors (Grossman and Helpman, 1991; Sachs and Werner, 1999; Rodriguez and Rodrik, 2001).[34] Our results therefore support the positive effects of openness on growth through technology spillovers for high-growth countries, as well as the composition and market/institutional imperfections arguments for low-growth countries in regime *C*. We do not find unequivocal support for the export-led-growth hypothesis in our sample. Cross-sectional studies that rely on the `average' country thus appear to obscure the importance of different growth regimes and the potential heterogeneity within a regime.

The output growth decomposition thus leads to several important conclusions. Though the forces that drive growth differ across regimes, capital accumulation is consistently an important component of growth across all the regimes. This finding is consistent with the results of several prior studies (Koop et al., 1999, 2000; Koop, 2001; Limam and Miller, 2004; Davis et al., 2007). However, it differs from Solow (1956) who found that capital accumulation accounts for between one-eighth and one-quarter of total output growth in the United States, whereas productivity accounts for more than half of output growth in most other countries.[35] We find instead that growth in high- and medium-growth countries across all regimes results from technical change, and growth in low-growth countries is mainly driven by factor accumulation. Therefore, we find support for the technical change-driven growth explanation. Overall, our results do not support a uniform explanation of growth.

The set-up of our model allows countries to switch regimes. A simple way to shed more light on the factors that determine regime migrations is to test if the covariates we used to predict group membership differ significantly between those countries that move and those that stay within regimes. In Table 8 we indicate whether, for those countries that change regimes, each of the conditioning variables is significantly different than the values for the rest of the countries in the regime from which the country has departed. We use two tests: a parametric t-test and a non-parametric Kruskal-Wallis rank test. Table 8 reports the p-values from these tests for each transition depicted in Table 5. The number of observations equals the number of countries moving (e.g., 42 moving from A to B) multiplied by the number of years in the period prior to moving (e.g., 5 such that N=42x5=210). A positive (negative) sign indicates that the conditioning variable is higher (lower) than that of the other countries in the regime. For example, in the second column of the first section of Table 8, the p-values of 0.0104 and 0.0042 and significance levels of 5% and 1% indicate that countries that moved from regime A to regime C had significantly lower human capital levels than did countries that remained in regime A.

[34] According to Grossman and Helpman (1991), a country may specialize in a non-dynamic sector as a result of its openness, which causes it to lose out on the long-run benefits of increasing returns. The underlying imperfection involves the contracts or financial markets that induce people to follow a myopic notion of static comparative advantages. Sachs and Werner (1999) also develop a model in which specialization in extractive, natural-resource sectors diverts the economy from achieving technological progress. In this case the underlying imperfection is the institutional weakness that encourages natural-resource depletion for quick gains among only certain societal groups. Finally, Rodriguez and Rodrik (2001) review the theoretical arguments regarding why openness might be detrimental to developing countries.

[35] Christensen and Cummings (1981), Dollar and Sokoloff (1990), King and Levine (1994), and Kim and Lau (1996) report similar results.

Table 8
Migrating countries and their regime determinants

Movement	*A* to *B*	*A* to *C*	*B* to *A*	*B* to *C*	*C* to *A*	*C* to *B*
(N)	(210)	(25)	(185)	(10)	(40)	(30)
			Human capital			
sign	+	-	-	-	+	-
t-test	0.3239	0.0104**	0.0000***	0.0000***	0.0056***	0.9765
rank test	0.1523	0.0042***	0.0003***	0.0000***	0.9465	0.3484
			Financial development			
sign	-	-	-	-	-	+
t-test	0.0841*	0.0015***	0.6749	0.0000***	0.5140	0.0002***
rank test	0.8435	0.0000***	0.8185	0.0000***	0.9233	0.0005***
			Primary sector share			
sign	-	+	-	+	-	-
t-test	0.1276	0.0003***	0.1293	0.0000***	0.0000***	0.0378**
rank test	0.0062***	0.0001***	0.3351	0.0000***	0.0000***	0.0415**
			Openness to trade			
sign	+	+	-	+	+	-
t-test	0.9494	0.0000***	0.1817	0.8936	0.7739	0.0231**
rank test	0.4874	0.0000***	0.0007***	0.8955	0.4589	0.0227**

Significance at the 10/5/1% levels (*/**/***).

From the last two columns of Table 8, we observe that increases in financial development (for migrations to regime *B*) and human capital (for migrations to regime *A*) are important strategies with which countries can `escape' from regime *C*. In addition, as countries in that regime develop, their primary sector share decreases, and they may become less dependent on exports (resulting in a lower openness to trade as it is measured here). This too makes countries in regime *C* more likely to move to migrate to regimes *A* and *B*. Countries that migrate from regime *B* to regimes *A* have a relatively low level of human capital. In addition to human capital, a poor financial development and a relatively large primary sector share contribute to migrations from regime *A* and *B* to regime *C*.

Yet regime migrations are not the only way in which countries can improve their performance. Within each regime, less technologically advanced countries can grow faster than advanced ones because they only need to copy the technology of the latter. This notion underlies much of the convergence literature. In their review of the convergence literature, Durlauf et al. (2005) find that the estimation of convergence rates can be improved by augmenting the Solow-Swan model with human capital (Mankiw et al., 1992), by considering regional convergence clusters (Mankiw, 1995; Quah, 1996), and by employing econometric advancements such as panel data analysis (Islam, 1995). Still, many studies continue to find either no or considerably different convergence rates.

A possible explanation for this persistent convergence puzzle may be the neglect of different regimes. Countries may converge (at different rates) within but not necessarily across regimes, as we argue here. To test for convergence, we replicate the modeling and estimation approach of the seminal work of Mankiw et al. (1992). We only differ from the original analysis of Mankiw et al. (1992) in one respect. We not only test for convergence for the whole sample, but also for each of the regimes identified by our conditional latent

class model. To examine convergence we estimate the following convergence equation from
Mankiw et al. (1992):

$$\ln\frac{y(t)}{y(0)} = (1-e^{\lambda T})\frac{\alpha}{(1-\alpha)}\ln(s) - (1-e^{\lambda T})\frac{\alpha}{(1-\alpha)}(n+g+\delta) - (1-e^{\lambda T})\ln(y_0), \quad (6)$$

where y is output per worker, t and 0 indicate the end and start of the respective period, s is the share of income saved and assumed to be invested, and δ and g denote the exogenous depreciation, respectively. Following the convergence literature, we choose a joint rate for δ and g of 6%.[36] The working population evolves at rate n, which we observe from the data. According to the last term in equation (6), countries with lower initial output per worker should grow faster. The pace of convergence is implied by λ.

We estimate equation (6) for all countries during the whole sample period, as in Mankiw et al. (1992), as well as for each five year period, as in Barro and Sala-i-Martin (1992). Subsequently, we repeat the estimations for each regime.

The top panel of Table 9 reports the estimates of equation (6) for the full sample of 77 countries during the period 1970-2000 and for the six sub-periods. The initial income coefficient is negative and in line with theory. The diagnostics (sample size and R^2) indicate fairly good explanatory power. For the whole sample period the annual convergence rate implied by a λ of 2.4% is in line with previous evidence.[37]

Our conjecture that the existence of different regimes has important implications for convergence also receives support from the regime-specific parameters. Long-run estimates of initial income coefficients, reported in the rightmost column of Table 9, imply convergence rates that range from 2.1% in the fairly developed regime B to 4.4% percent in the poorly performing regime C.[38] Since laggard countries are predicted to converge faster, this illustrates that imposing the assumption of an identical steady state underestimates convergence rates for some, mostly less developed, countries. The key finding of this analysis is that countries converge to their own regime-specific steady state and the rate of convergence differs from regime to regime.

Convergence results per regime across the whole sample period are also subject to a caveat. Grouping countries to one regime for the entire period requires allocations based on mean regime memberships. A country that appears in regime A for three intervals and then three intervals in group C would be allocated to regime B.[39] Most countries do not switch regimes, which can mitigate some of these concerns. We can account more explicitly for possibly different convergence speeds. To this end we estimate equation (6), similar to Barro and Sala-i-Martin (1992), for each of the different episodes in the latent class frontier model to identify the regimes.

[36] Changing $(\delta + g)$ between 2.5% and 9.5% in increments of fifty basis points does not not alter our results qualitatively.
[37] Overall, the other coefficients are also consistent with theoretical predictions: faster population growth reduces the growth of per worker income and higher savings facilitate growth significantly.
[38] See Islam (1995), Caselli et al. (1996), and Jones (1997) for evidence.
[39] Results shown here are based on the arithmetic mean of the groups to which the countries are allocated during the maximum of the six periods, as shown in Table A.3 in the Appendix.

Table 9
Convergence regressions

variable	*1970-1974*	*1975-1979*	*1980-1984*	*1985-1989*	*1990-1994*	*1995-2000*	*1970-2000*
				All			
$\ln y_0$	-0.029	-0.062***	-0.085***	-0.086***	-0.024	0.005	-0.528***
$\ln(n+g+\delta)$	0.104	0.052	-0.319*	-0.495***	-0.105*	-0.340***	-0.532
$\ln(s)$	0.075*	0.050	0.100	0.130***	0.143**	-0.085***	1.056***
$\ln\alpha$	0.423	0.471*	-0.674**	-1.234***	-0.484***	-0.477***	-2.119**
N	45	50	58	65	74	76	77
R^2	0.060	0.181	0.198	0.521	0.259	0.196	0.563
implied λ	0.006	0.013	0.018	0.018	0.005	-0.001	0.024
				Regime A			
$\ln y_0$	-0.037	0.025	-0.187***	-0.141***	-0.053	-0.043	-0.663***
$\ln(n+g+\delta)$	0.478*	-0.221**	-0.208	-0.694***	-0.266***	-0.392***	-0.998**
$\ln(s)$	0.153	-0.110	0.251***	0.197**	0.074	-0.027	0.962***
$\ln\alpha$	1.204*	0.073	-0.560	-1.737***	-0.598***	-0.623**	-2.664***
N	21	13	21	21	27	29	51
R^2	0.201	0.439	0.543	0.642	0.502	0.198	0.756
implied λ	0.008	-0.005	0.041	0.030	0.011	0.007	0.035
				Regime B			
$\ln y_0$	-0.126**	-0.099***	-0.122***	-0.100***	-0.085***	0.005	-0.482***
$\ln(n+g+\delta)$	0.032	0.019	-0.269	-0.501***	-0.121**	-0.417***	-0.485
$\ln(s)$	0.139**	0.043	0.209***	0.121*	0.220***	-0.040	0.999***
$\ln\alpha$	0.216	0.480	-0.759*	-1.194***	-0.568***	-0.812**	-2.066
N	16	26	26	37	36	36	17
R^2	0.373	0.491	0.445	0.466	0.463	0.301	0.584
implied λ	0.027	0.021	0.026	0.021	0.018	-0.001	0.021
				Regime C			
$\ln y_0$	-0.293*	0.220	-0.155	0.026	-0.007	0.263	-0.747***
$\ln(n+g+\delta)$	-1.580**	0.133	-2.863*	-0.384	0.408**	0.080	-1.302***
$\ln(s)$	0.164**	0.116	0.186	0.081	0.069	-0.158	-0.001
$\ln\alpha$	-3.974**	0.378	-7.307*	-0.991	0.824	0.546	-2.252**
N	8	11	11	7	11	11	9
R^2	0.726	0.55	0.499	0.671	0.434	0.443	0.852
implied λ	0.069	-0.040	0.034	-0.005	0.001	-0.039	0.044

Ordinary least square estimates of equation (6); $\ln y_0$ is the log of initial per capita output; the savings rate, s, is approximated by the investment share of GDP in fixed capital; $\delta + g = 0.06$; n is the observed average annual growth of the working population; the number of observations is in parentheses. Significance at the 10/5/1% levels (*/**/***).

The pertinent columns in Table 9 confirm the dispersion of convergence rates.[40] In regime *B* there is convergence across most periods at a pace of 2%. In contrast, the fully efficient and primarily technological change-driven regime *A* only exhibits signs of strong convergence during the 1980s. The absence of significant estimates of convergence in each period in regime *C* likely reflects the low number of observations.

[40] The additional effects of saving and population and technical change, as well as depreciation, differ too. Here we focus on the implications of different technology regimes for income convergence.

Overall, aggregate convergence might be deceptive to the extent that within-regime estimates differ significantly across both regimes and time periods. Our results thus might explain why some studies continue to find mixed evidence about the existence and magnitude of convergence. That is, it may be due to their neglect of different regimes.

5. Conclusion

The standard neoclassical growth literature assumes that: (i) countries use resources efficiently, and (ii) that the underlying production technology is the same for all countries. In this paper we address these issues by estimating a stochastic frontier model augmented with a latent class structure. Hence, we explicitly account for inefficiency and allow for production technologies to differ across groups of countries. In contrast with many cross-country growth studies, we estimate membership in groups instead of determining *ex ante* which countries should be compared.

Our empirical analysis is based on a sample of 77 countries over a thirty-year period. The results support the existence of three regimes of countries. First, a large, or mature regime that is comprised of many mature economies, such as the U.S. and European countries. It is characterized by high output per capita, high human capital accumulation, high capital elasticity, and some level of inefficiency. The second regime, the emerging regime, contains primarily emerging (developing) countries, mostly Asian, and is characterized by productive labor, relatively well-developed financial system, and a high efficiency level. Finally, the third regime, the developing regime, includes the least developing countries, mostly African, and is characterized by very low output per capita, a high degree of openness to trade, a large primary sector share, and high inefficiency.

The driving forces of growth vary across regimes also. Growth in the mature regime depends primarily on factor accumulation in general and capital in particular, whereas the key generator of growth in the emerging regime is (pure) technical change. Growth in the developing regime depends on both (pure and labor-augmenting) technical change and the accumulation of labor. Overall, our results support a rather pluralistic explanation of growth experiences in the countries in our sample. We also find evidence that input accumulation is a reasonable description of the growth process for some countries (in certain regimes) and of productivity (efficiency and technology) developments for others.

Our findings strongly suggest several different growth processes, which means that one-size-fit-all policy prescriptions based on standard one-class results cannot prescribe the right medicine for any country. More education alone, for instance, may put countries in more advanced regimes, but for education to be effective other development measures, such as enhanced factor allocation, financial development, or trade policies, are required.

The presence of fairly persistent and economically significant inefficiencies in the operations of best-practice technologies, especially in the regime with mostly developing countries, has important policy implications. For countries in the developing regime, development efforts geared toward developing the skills to exploit existing technologies may be better than promoting the dissemination of new technologies alone. Further research into the relative costs and benefits of policies promoting either technical change or efficiency improvements is warranted.

This implication ties in with our finding regarding the dynamics of regimes, which we investigate by accounting for regime migrations. Few countries appear able to maintain their upgrades to faster growing regimes. Because the determinants of group membership do not differ significantly between countries that shift regimes and those that stay, we believe that additional research into the determinants of regime switches, rather than membership would be fruitful. Our results show that most migrations pertain to countries switching between the mature and the emerging regime. The intra-group convergence patterns also reveal that countries from the mature and emerging regimes primarily improve by catching up with the leader countries in their own groups. Among the least developing economies though, such catch-up patterns are absent. Both the periods and pace of convergence differ, at times substantially, ranging between 1.8% and 4.1% per year. Thus, we find evidence of convergence to their own regime for most countries, but our results support in particular different convergence clubs around the world.

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Appendix

Table A.1
Specification tests for determining the number of regimes

Model	Conditional	Log likelihood	AIC	BIC
3-regime latent class frontier	no	1018.390	-1894.790	-1500.280
2-regime latent class frontier	yes	639.791	-1177.580	-894.205
3-regime latent class frontier	yes	1119.540	-2081.080	-1642.120
4-regime latent class frontier	yes	- no convergence -		

Akaike Information Criterion (AIC) = $\ln AIC = 2m - 2\ln LF(z)$, Schwartz Bayesian Information Criterion ($SBIC$) = $-2\ln LF(z) + m \cdot \ln(n)$; $LF(j)$ is the likelihood value for Z groups, m is the number of parameters in the model, and n the number of observations. The preferred specification has the lowest AIC or the lowest $SBIC$. See also Orea and Kumbhakar (2004).

Table A.2
Tests for equality of parameters between regimes

Regimes	Variable(s)	Test	Statistic	p-value	Hypothesis
Latent regime parameters					
A and B	translog production function	Wald	40.983	0.000	rejected
A and C	translog production function	Wald	7.261	0.007	rejected
B and C	translog production function	Wald	14.240	0.000	rejected
A, B and C	translog production function	Wald	50.456	0.000	rejected
Ancillary parameters on production traits					
A and B	capital elasticity ($\epsilon^K_{it\|z}$)	t-test	-16.754	0.000	rejected
A and C	capital elasticity ($\epsilon^K_{it\|z}$)	t-test	47.183	0.000	rejected
B and C	capital elasticity ($\epsilon^K_{it\|z}$)	t-test	52.170	0.000	rejected
A and B	labor elasticity ($\epsilon^L_{it\|z}$)	t-test	14.316	0.000	rejected
A and C	labor elasticity ($\epsilon^L_{it\|z}$)	t-test	-10.326	0.000	rejected
B and C	labor elasticity ($\epsilon^L_{it\|z}$)	t-test	-20.460	0.000	rejected
Regime membership probability parameters					
A and B	Human capital (H)	Wald	0.057	0.811	not rejected
A and B	Financial development (F)	Wald	144.980	0.000	rejected
A and B	Primary sector share (P)	Wald	0.020	0.888	not rejected
A and B	Openness to trade (T)	Wald	6.360	0.012	rejected
A and B	H, F, P and T	Wald	183.553	0.000	rejected

Null hypothesis tested at the 5% significance level is the equality of parameters between classes. Means and standard deviations for ϵ^K_{it} and ϵ^L_{it} can be found in Table 4. Coefficients and standard errors for H, F, P, and T can be found in Table 2.

Table A.3
Regime membership

Period	**70-74**	**75-79**	**80-84**	**85-89**	**90-94**	**95-00**	**Period**	**70-74**	**75-79**	**80-84**	**85-89**	**90-94**	**95-00**
Country			*Region*				*Country*			*Region*			
			Africa							*Americas*			
Algeria						B	Argentina				B	B	A
Benin					C	C	Bolivia			B	B	B	B
Botswana		C	A	A	B	B	Brazil					B	A
Cameroon	A	B	A	A	B	B	Canada	B	A	A	A	A	B
Congo, Republic of					C	C	Chile	A	B	B	A	A	A
Egypt		A	A	A	A	A	Colombia	A	A	A	A	A	A
Gambia, The		C	C	C	A	C	Costa Rica	B	B	A	B	B	B
Ghana	C	C	C	B	B	B	Dominican Republic	B	B	B	B	B	A
Kenya	C	C	C	C	B	B	Ecuador	A	B	B	B	B	B
Lesotho	C	C	C	C	C	C	El Salvador	B	A	A	A	A	A
Malawi			C	C	C	C	Guatemala	B	A	A	A	A	A
Mali				C	C	C	Guyana						C
Mauritania					C		Honduras	A	C	A	B	B	B
Mauritius			A	A	B	A	Mexico	B	A	A	A	A	B
Mozambique					A	A	Panama			A	B	A	B
Rwanda	C	A	B	B	C	C	Paraguay	B	B	B	B	A	B
Senegal	C	C	C	B	B	B	Peru				B	B	B
South Africa	A	B	A	A	A	A	Trinidad &Tobago			B	A	B	A
Togo	C	C	C	A	C	C	United States	B	B	B	B	B	B
Tunisia				B	A	A	Uruguay			A	B	A	A
Uganda			C	C	C	C	Venezuela	A	B	B	B	B	B
Zambia				C	C	C							
			Europe							*Asia*			
Austria	B	B	B	B	B	B	Bangladesh					A	A
Belgium	B	B	B	B	B	A	Hong Kong						A
Denmark	B	B	A	B	B	B	India	A	A	B	B	A	B
Finland	A	B	A	B	A	B	Indonesia	A	B	C	A	A	A
France	A	A	B	B	B	A	Iran	A	A	A	B	B	A
Germany					B	A	Japan	A	A	A	A	A	A
Greece	A	B	A	B	B	B	Jordan		C	B	A	B	B
Hungary			B	B	B	B	Malaysia	A	B	B	B	A	A
Iceland	B	A	C	A	C	A	Pakistan	C	C	B	A	A	A
Italy	A	A	B	B	B	B	Philippines	A	B	B	B	B	B
Netherlands	B	B	B	B	B	A	Sri Lanka	A	B	B	B	B	B
Norway	B	B	B	B	A	B	Syria				A	A	A
Poland					B	B	Thailand	C	C	C	B	B	B
Portugal	A	B	B	B	A	B	Turkey				A	A	A
Spain	A	B	A	B	B	B				*Oceania*			
Sweden	B	B	B	B	B	B	Australia	B	B	B	B	B	A
Switzerland					A	B	New Zealand		B	B	B	B	B
United Kingdom	A	B	A	A	A	B							

Notes: Most likely regime membership allocations per five-year period to the emerging (A), mature (B), and developing (C) groups. Probabilities obtained from Equation (4) conditional on period averages of human capital, financial development, primary sector share, and openness to trade. Total (annual) observations per regime A, B, and C, respectively, are 689, 919, and 305.